Skills, Tasks and Mismatch: Three Essays in Empirical Microeconomics

Aspasia Bizopoulou

Doctor of Philosophy

The University of Edinburgh

School of Economics

2018

Declaration of Own Work

I declare that this thesis was written and composed by myself and is the result of my own work unless clearly stated and referenced. Chapter 3 is co-authored with fellow PhD student Rachel J. Forshaw. I made substantial contributions to the third chapter, including towards the origin of the research question, the coding and data handling, the methodology, the estimation, the interpretation of results and the writing of the paper. This thesis has not been submitted for any other degrees or professional qualifications.

Aspasia Bizopoulou

19/4/2019

To my parents, Tassos and Alexandra, and to my husband, Tom.

Acknowledgments

I would like to thank my advisor Maia Güell for always having an open door when I needed guidance with the thesis. I am grateful to Maia for making time to meet me regularly, for her countless suggestions for improving my drafts, for alerting me about relevant conferences and for patiently guiding me throughout the four years of the PhD. I am also grateful for the additional time she took to prepare me for the key moments of the PhD, from the 1st year review all the way to the flyouts, which eventually led to a job offer. Without her I would not have been able to navigate the PhD, let alone obtain a post-doc. I was lucky enough to have not one, but two second advisers throughout the course of my PhD at Edinburgh. First, Philipp Kircher sparked my interest in the literature for mismatch and guided me early on in the writing of my research proposal, in reading the right papers and keeping up my interest in the topic. Later, Liang Bai helped me hone my writing and was there for advice when I was uncertain about post-PhD careers. I thank all three of my advisers for their patience and belief in me, even during those moments I didn't prove to be as quick or organised or smart as they might have hoped. Finally, I would like to thank my PhD viva examiners, Raquel Carrasco and Ludo Visschers for carefully reading my thesis and providing me with a plethora of comments to help me improve it - and my post-doc adviser, Tuomas Pekkarinen, for his extensive and thoughtful comments on all chapters of this thesis as well as tips on how to survive the viva!

Additional thanks are due to Ludo Visschers for his comments on the 3rd chapter of the thesis, especially when we got caught up for several months in what turned out to be an original mistake in the raw data. I am also very grateful to Ed Hopkins and Tatiana Kornienko for allowing me to join in their weekly discussion group on behavioural economics, even though I'm not a behavioural economist. I thoroughly enjoyed discussing the seminar of the week, as well as learning about a plethora of other interesting research through the learned and critical eye of both Ed and Tatiana. I am also grateful to Andrew Clausen for all his help during the academic job hunting process, including organising mock interviews and practice talks, giving me website tips and introducing me to the concept of the 'elevator pitch'.

I would also like to thank my dear friend, co-author and office mate, Rachel Forshaw. It has been really great working with you and I have learned so much from you about macroeconomics, calibration methods and how to write better code. Who would have known that what was originally a shopping trip to Bordeaux would turn into a research project, with us discussing economics during the entire plane journey back home. You know it's a good shopping trip when it results in a new project! Thanks also to Sarah Schroeder for the many discussions we had on the search literature, it was really helpful to read and discuss papers together. Additional thanks go to Ina Taneva and Alessia de Stefani for sharing their passion on gender issues with me and for the numerous interesting discussions we had on the topic.

A big thank you to office 3.01, for all the fun discussions touching on everything from how to reform the NHS, to gender gaps, to the merits of veganism. Cischi, Cristina, Johannes, Rachel, Sergei, Tomasz, and also Carlotta and Olga, it has been amazing to have a room full of fun and understanding office mates, always there to celebrate the good times, the bad times and have a laugh about the stuck-up culture of economics :D. Thanks Cischi for always having a good joke under your sleeve and knowing where to eat good and cheap food. Thanks Cristina for Stata and Python help, cake bake-offs and listening to me while I sleep talked in our shared room at conferences. Thanks to Johannes for Stata help and the numerous discussions on a wide range of subjects, on which we didn't always agree (but are still friends, hopefully!). Thanks to Rachel for lessons in coding efficiency and style, hilarious jokes and for always knowing how to make me feel better. Thanks to Sergei for organising the amazing Econteering events, teaching us the dance moves and his passion for teaching. Thanks to Tomasz for being so kind and thoughtful, for all the good advice and for always being there to listen when things were a bit tough. Thanks to Carlotta for the energy and excellent stories she brought at each of her visits and thanks to Olga for always being there to listen and quickly analyse the situation. Thank you also to Yulia for the excellent brownies and the dance moves and to Camille, Andre and Marcel for impromptu dinners and lovely picnics in the park. And thanks everyone for some excellent board game and poker nights!

I am also grateful to Emily & Annelise Kempton for generously hosting us in their house for 3 months and for the countless brunches and afternoon teas we had together. I am grateful to my long-time friend, Kate, who was there to host me in Paris when I needed to escape the northern bleakness and helped make the daunting task of completing the thesis a little bit easier - and to my long-time friends Natalia, Georgia and Angela for hosting me in Greece while I was collecting data. Special thanks to Tal for sharing with me her tales of adventures in faraway lands and for always being up for a good girl-power chat. Thanks to all the friends who have brought me joy over the last four years: Joke, Jonas, Tim, Helene, Ophelie, Marie-Astrid, Jon, Rayna, Patrick, Chen, Eleni, Zac and the old economics crew from Utrecht: Bram, Julia, Kasia, Mathijs, Michalis, Nils, Tim, Zori.

I would like to thank my parents, Alexandra and Tassos, for having championed my education from when I could barely walk and for having unconditionally supported any decisions involving more education, both psychologically and financially. Finally, I would like to thank my wonderful husband, Tom Kempton, for his love, unconditional support, academic advice and endless patience throughout the entire PhD, and especially over the final months.

Abstract of Thesis

This PhD dissertation examines the role of job tasks as a means to explaining wage inequality in the labour market. In the first chapter I study whether we can improve our understanding of labour market mismatch and its consequences for wages by augmenting current measures of mismatch with task information. In the second chapter, I look at whether task-and-skill augmented mismatch is substantially different for men and women. In the third chapter, I study whether individuals' job tasks and their level of difficulty change when they make transitions in the labour market and the extent to which these changes are affected by recessions.

Chapter 1. Job Tasks and Mismatch within Occupations I propose a new multi-dimensional measure of mismatch derived from individual-level information on skills and tasks. Previous measures have either entirely excluded information about tasks or have used tasks aggregated at the level of the occupation, rather than at the individual level. I find that across nine European countries, up to 24% of the population is mismatched in literacy and 15% in numeracy. I also find that for Northern European countries, extreme levels of skill-task mismatch are negatively correlated with wages and the correlation persists within occupations. Southern and Central Europe do not appear to exhibit any correlation between mismatch and wages, either between or within occupations. Subsequently, I compare the new measure to existing measures of mismatch from the literature. I find that measures based on higher levels of data aggregation or measures excluding the role of tasks tend to consistently under-estimate the cross-sectional correlation between mismatch

and wages.

Chapter 2. Gender and Mutli-dimensional Mismatch Using a measure of multi-dimensional mismatch developed in chapter 1, I compare mismatch in literacy and numeracy among men and women in the labour market in a sample of 9 European countries. Previous studies on multi-dimensional mismatch have used male-only samples due to a lack of individual-level data about female skills and tasks. I discuss a set of stylised facts about literacy and numeracy mismatch for men and women: men and women have similar levels of mismatch in literacy but not in numeracy, with women experiencing less negative mismatch. In terms of outcomes, men and women are affected by mismatch in similar ways: in most countries their earnings are negatively affected by being under-skilled in either literacy or numeracy. Women appear to show a slightly greater advantage than men at being over-skilled in numeracy. Finally, I find that mismatch does not help explain part of the gender earnings gap in a traditional Mincer model.

Chapter 3. The Task Content of Occupational Transitions over the Business Cycle: Evidence for the UK We study the change in the task content and the extent of up- and de-skilling of occupational transitions over the business cycle for the UK. Previous literature shows that during recessions individuals are less likely to move occupations - yet it is unclear whether their task portfolio and the skill level of tasks also changes during the cycle. We use quarterly data from the U.K. Labour Force Survey, which we match to the O*NET dictionary of tasks for the period 1997q1 - 2016q2. We find that during recessions, individuals tend to move to more similar occupations in terms of tasks and they are also less likely to experience an increase in the skill requirements of their new jobs.

Lay Summary

One of the major themes that preoccupy economists is whether available resources in production are efficiently allocated. For example, a bottle-making factory might consider purchasing an additional machine to speed up bottle-making in the production line. An economist will question whether the current demand for bottles faced by the factory gives good reason for wanting to produce more bottles per day: will the factory end up producing too many bottles, so much so that revenue will be lower than when it produced fewer bottles? Or does it still need to buy even more machines to meet current demand? Finding the optimal level of production that meets demand without wasting any resources or decreasing revenue brings *efficiency* to the production process: resources are used to their optimal capacity and there is no waste. Similar questions arise when thinking about how many people a café might employ: it will consider how many baristas it needs behind the counter to efficiently serve clients without long queues, but also without too many baristas relative to clients.

In the above examples, the units of measurement of the *inputs* relative to the *output* are very clear: how many bottles does each machine produce or how many baristas are required to serve a number of clients in a given time. Using tools of optimisation, one can calculate the most efficient way to organise the resources required for production. However, efficiency is much harder to achieve when the resources required for production are harder to quantify, such as higher level human cognitive and manual skills. Complex human skills such as mathematical reasoning,

dexterity and creativity are extremely valuable to production, yet are much more difficult to measure in terms of their productivity. Moreover, assigning individuals to activities that are not suited to their skills can lead to enormous inefficiencies that can have knock on effects on both the firm and the individual and can ultimately lead to misjudged investments, bankruptcies and unemployment. With the rise of educational attainment and the increased demand for more complex skills in the workplace, the study of efficiency of allocation of skills to work tasks has become more urgent.

One way to think about inefficiency in the context of human skills is to study how well the specialisations of individuals match the activities they perform in their job. For example, how much output is lost when someone with good humanities skills works in a job requiring numeracy skills? The possibility of such misalignment is referred in the literature as 'mismatch', and the research focus is on understanding how to best measure mismatch, what are its consequences for individual earnings and firm productivity and where it might originate from. In this thesis, I improve on our understanding of the role of mismatch for individuals' earnings and career trajectory. Using empirical tools, I improve on current measures of mismatch; I provide new stylised facts on the levels and effects of mismatch for men and women separately; and I study how individuals' daily work activities are affected by recessions.

Chapter 1: One of the building blocks of the mismatch literature is how it is measured in the first place. Different levels of data availability over the years have led to increasingly more precise tools, which take into account not only the individual's level of education relative to that of the job requirements, but also how their exact skill level compares to the job's day-to-day tasks. Such improvements in data allow for studying how good is the match between the individual and the job in multiple dimensions, like in numeracy or in literacy, rather than only looking at overall education. However, evidence on the individual skills and daily tasks of a working individual remains sparse due to datasets not usually providing information on both daily job activities and skills of the individual. In the first chapter, I create a new measure of mismatch which can account for the individual's skill score in literacy and numeracy dimensions and compare it with their level of engagement with literacy and numeracy tasks at their job. I then compare the measure of mismatch I propose with two recent measures from the literature that are much less precise in the measurement of daily tasks. I find that in Northern European countries, the additional precision of my measure highlights the contribution of one's daily activities on the impact of being mismatched on earnings, over and above the importance of one's job title specialisation.

Chapter 2: Although the increased availability of better data has tremendously improved our understanding of the consequences of being in the wrong job, the study of women's careers has been largely left out of the recent data advances. The oversight has been one of chance rather than design, since studies of mismatch that use skill data are based on administrative registers containing test information from military conscription, which women are not eligible for in most countries. In my second chapter, I provide the first comparison of stylised facts on multi-dimensional mismatch for men and women, using skill information from both. I find that men and women have similar levels of mismatch in literacy, but not in numeracy, where women are much less likely to be under-skilled relative to men in nine European countries. Nevertheless, the outcomes of being mismatched on earnings are similar for both men and women: in most countries mismatch does not affect earnings, except in Northern Europe where being under-skilled will negatively affect the earnings of both men and women. Finally, accounting for the level of female mismatch does not help in further explaining the gender wage gap between men and women.

Chapter 3: While in the first two chapters I study mismatch and its consequences at one point in time only, in the third chapter, together with my co-author Rachel J. Forshaw, we extend the tools of mismatch to the study of job-to-job transitions by individuals in the UK for a period of almost 20 years, including during the years of the 2008 recession. The recession affected all aspects of economic life, yet little evidence exists on how it affected the knowledge content of jobs of new hires, which directly impacts the possibility of mismatch. We study the change in knowledge content of jobs, both in terms of subject matter and difficulty level, for all individuals making a job transition between 1997 and 2016. We find that in worse economic times, as identified by higher levels of unemployment, individuals tend to move to jobs closer in subject matter to what they did before. Furthermore, the movement towards harder and more challenging jobs in terms of skill requirements is significantly slowed down during recessions.

Contents

List of Figures

List of Tables

Chapter 1

Job Tasks and Mismatch within Occupations

1.1 Introduction

Mismatch has been shown to generate inefficiency in more than one way. For example, being mismatched early on in one's career can have large follow-up costs, depending on initial skills. Lise and Postel-Vinay (2016) show that workers could gain 8-22% higher output over their lifetime, if allowed to enter a better match early on. Fredriksson et al. (2018) find that higher levels of mismatch lead to more separations in the labour market - in particular for inexperienced workers, while Guvenen et al. (2015) show that verbal mismatch is correlated with slow wage growth over the course of the match.

One the building blocks of the mismatch-related literature is how mismatch is measured in the first place. Early literature focused on uni-dimensional measures such as years of education, or self-reported measures.[1] More recent years have seen the introduction of multi-dimensional measures, where for each individual observation the data offers more than one measure of mismatch. For example, for each

[1] Examples of work using these type of measures include (Di Pietro and Urwin, 2006); (McGuinness and Sloane, 2011); (Badillo Amador et al., 2012); (Kampelmann and Rycx, 2012).

individual we may have a mismatch measure on their literacy skills and another on their numeracy skills. These measures are constructed using standardised tests (e.g. literacy, numeracy, social skills), which are then juxtaposed with skill requirements at the occupational level for each individual. Examples of papers using this type of mismatch measure include (Lise et al., 2013); (Fredriksson et al., 2018); (Guvenen et al., 2015); (Lindenlaub, 2017).

Current multi-dimensional measures, however, do not have information on job tasks at the *individual level*. For example, in Guvenen et al. (2015), all individuals working in the same occupation are assumed to be doing the same set of tasks for the same amount of time. In Fredriksson et al. (2018), the authors do not use task information at all. In other words, in current measures of mismatch, tasks are either ignored or are assumed to be perfectly correlated with the individual's occupational code. While it is not unreasonable to assume that individuals in the same occupation perform the same tasks, there are studies offering evidence against the assumption that tasks are uniformly distributed within an occupation: most notably, Autor and Handel (2013) show that the type of tasks performed in the same 1-digit occupation vary systematically by gender and race.

In this paper I propose a new measure of mismatch in which I incorporate information on the skills of the individual, as well as all their individuals job tasks, unlike previous mismatch measures. The aim of the measure is to use skill scores in literacy and numeracy and then compare those scores to how intensively individuals perform the tasks requiring those skills, relative to their peers within the occupation. More formally, I am able to compare individuals' position in the skill distribution to their position in the task intensity distribution of the corresponding tasks, within their 3-digit occupational category.

Using the new measure of mismatch, I test for the correlation between wages and mismatch both between and within occupations, controlling for demographic characteristics. While previous papers have studied the effect of mismatch on wages with the main source of variation coming from occupational switches, I can keep occupations constant and focus on mismatch based on variation from tasks portfolio and skill level of individuals in the same occupations.[2] Overall, I find that up to 24% of the working population are mismatched in numeracy, and up to 15% in numeracy, with the highest levels of mismatch in numeracy being in Northern Europe, while in literacy they are in Central Europe. I show that extreme levels of skill-task mismatch in numeracy and literacy within an occupation are negatively correlated with wages for Northern European countries but not for Southern or Central Europe. The negative correlation persists both between as well as within occupations for Northern Europe while it is not at all present between or within occupations for Southern and Central Europe. Thus, one of the contributions of this paper is to show that, when present, negative correlations of mismatch and wages persist even within occupational categories and that occupational choice is not necessarily the main driver of mismatch.

The second contribution of this paper is to offer a comparison of the new measure with existing multi-dimensional measures which either exclude tasks altogether or use occupation-level tasks only. In the first case, Pellizzari and Fichen (2017) develop a mismatch measure using the exact same dataset as here, but only based on the skills measures. Three match categories are defined based on self-reported information: the well-matched, the over-skilled and the under-skilled. Then, the skills scores of the well-matched within a 1-digit occupation provide the benchmark for who is truly well-matched. Thus if an individual's score within their 1-digit occupation is above or below the range of scores for the well-matched, then they are mismatched. Using this measure the authors find that at most 20% of individuals are mismatched in literacy. In contrast, by including tasks in the mismatch measure, I find that skill-task mismatch in literacy affects up to 24% of workers. Subsequently,I set the two measures against each other to observe how they correlate with wages. I find that

[2] Lise and Postel-Vinay (2016); Guvenen et al. (2015); Fredriksson et al. (2018) have all identified mismatch by studying occupational switching.

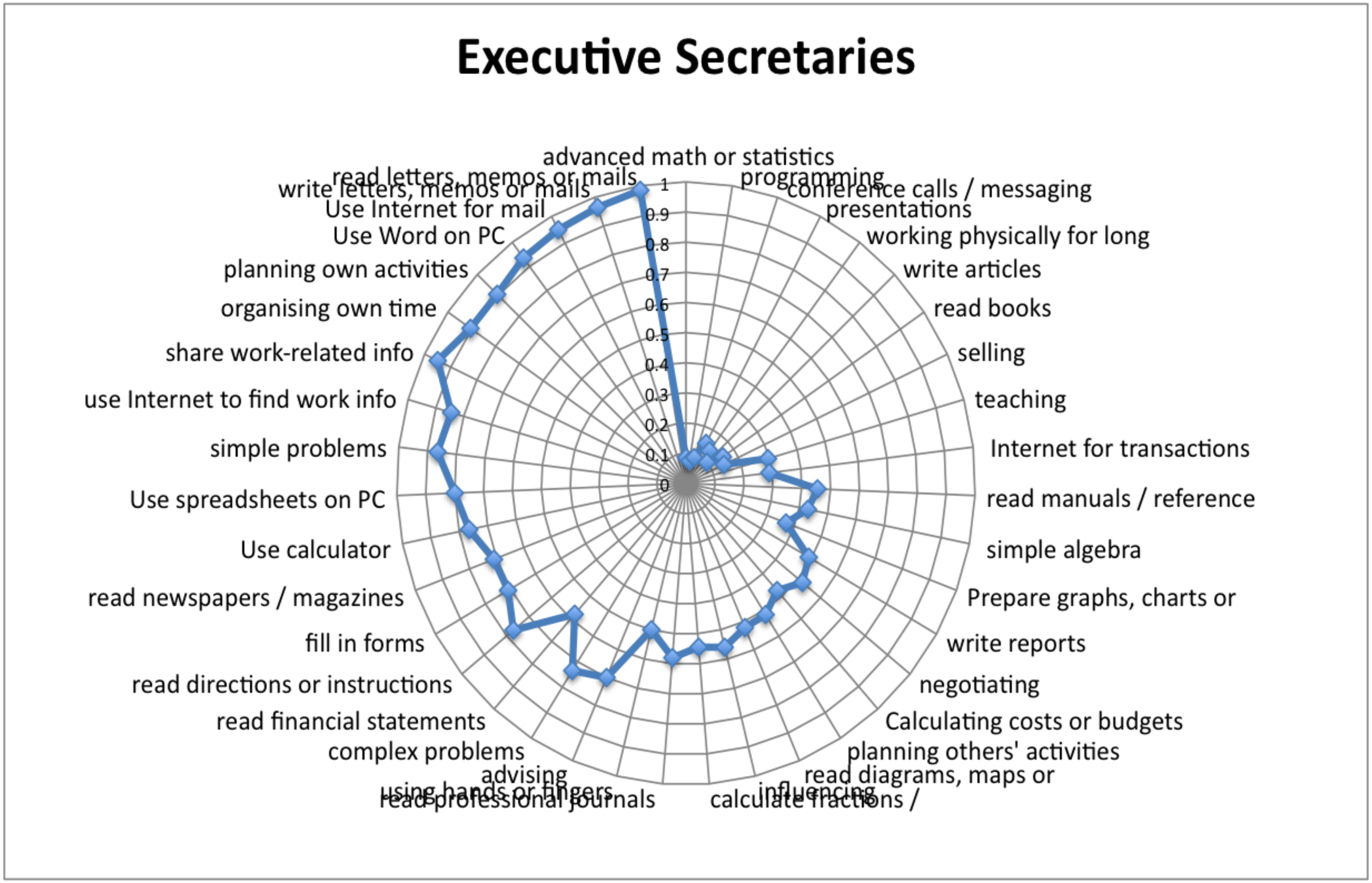


Figure 1.1: Distribution of tasks among Administrative and Executive Secretaries

being skill-task mismatched in literacy is strongly negatively correlated with wages. However, the correlation cannot be observed when using the measure by Pellizzari and Fichen (2017), even though the skill scores and the baseline dataset are the same.

The second comparison is done with a measure used by Guvenen et al. (2015). The authors develop a mismatch measure using skills and occupational tasks and subsequently test its impact on wages. The mismatch measure of Guvenen et al. (2015) is based on skill information at the individual level and task information at the occupational level. What the measure misses is information on tasks at the individual level - in other words, if two people work in the same occupation they will be assumed to have identical tasks at work in Guvenen et al. (2015), but not in the measure I propose. As can be seen in Figure 1.1, it is not necessarily the case that individuals in the same occupation do the same tasks. For example, when looking at Executive Secretaries, which is a 3-digit ISCO 2008 occupation category, we see that the task profile of workers in the same occupation is not homogeneous. In the comparison exercise I show that observing tasks at the occupational level only, will tend to under-estimate the effect of mismatch on wages.

One possible worry of the current study is the existence of measurement error. Several other papers have already used PIAAC and the issue of measurement error has arisen, in particular relating to the skills measures. In the original survey, three skills were measured: numeracy, literacy and problem solving. However, for each country, close 30% of the sample did not take the problem solving standardised test. Following the lead of other papers, I choose to not include problem solving in our skill mismatch measures, as it is not clear whether the 30% that did not take the problem solving test was systematically selected or random. Another potential source of measurement error are incomplete data on wages. For the UK sample, close to 40% of respondents choose to not reveal their wage, so I do not include them in the analysis. Finally, there is the issue of possible measurement error in the coding of occupations. Occupational categories across countries may be substantially different, due to the different rate at which countries are affected by technological change or to localised industry specialisation.[3] Nevertheless, the occupational coding used in PIAAC, the International Standard Classification of Occupations, is designed to be comparable across countries unlike country-level versions of occupational codes.

I use the Programme for International Assessement of Adult Competencies (henceforth PIAAC), a dataset that has been collected by the OECD, for the year 2013. PIAAC provides information from a representative sample of nine European countries about individuals' skills in literacy and numeracy as well as their daily job tasks. The skills scores are derived from a set of standardised tests which all participants undertake.[4] The tasks are based on self-reported accounts on the frequency of engaging in different activities on-the-job. The data also contains information on demographics, education and job-related characteristics.

The rest of the paper is organised as follows: in section 1.2 I provide a literature review; in section 1.3 I introduce the data; in section 1.4 I present the new measure; in section 1.5 I present some summary statistics on who is mismatched; in section 1.6 I write out the empirical model, present the results; in section 1.7 I run the comparison exercise with other multi-dimensional mismatch measures in the literature; and in section 1.8 I conclude.

1.2 Literature Review

The literature on mismatch is vast and spans several fields of study. This paper is closest to the strand focusing on mismatch in the labour market among already

[3]For example, the UK's 'Standard Occupational Classication' has been updated 3 times over 30 years and maintains a reasonably dis-aggregated list of occupations, with an average of 250 categories. France's 'Nomenclature des Professions et Catégories Socioprofessionelles' has been updated 3 times over 40 years, is less disaggregated than the UK's and the categorisation places higher importance on the profession's hierarchical status rather than the occupation's content. In Belgium, the francophone 'Nomenclature et codes des professions' is substantially more aggregated than what can be found in either France or the UK and devotes much less space to service professions, relative to the UK's SOC.

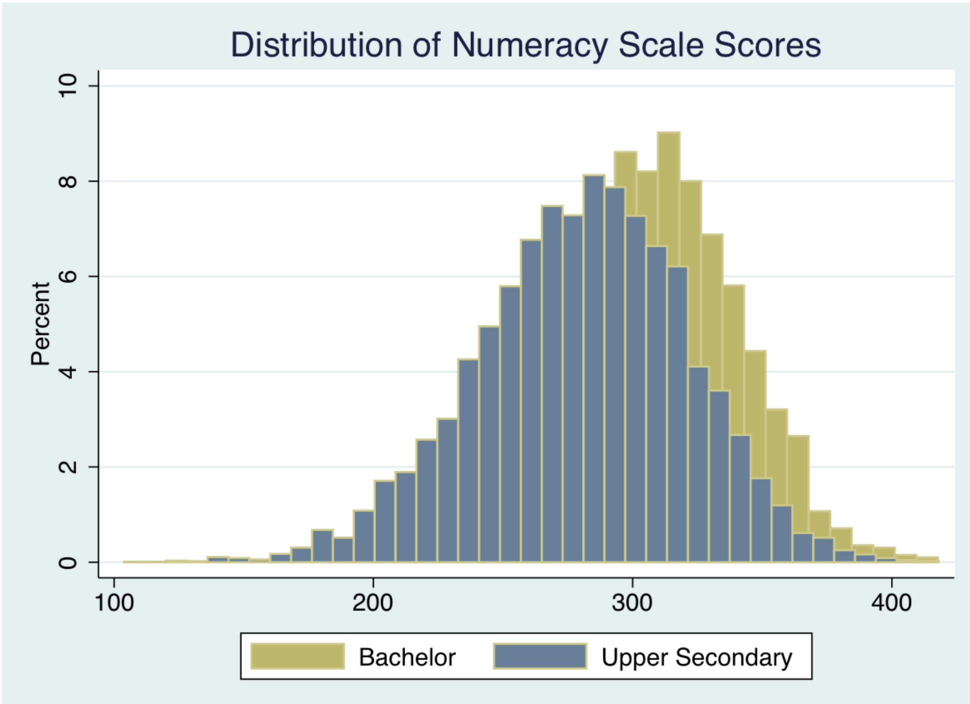
[4]For a more detailed explanation of the sampling technique, see Appendix A

employed workers. Within this area, research questions pertaining to mismatch can be broadly divided into three separate branches: i) why does mismatch happen; ii) how to measure it and; iii) how does it impact labour market outcomes. [5] The first question has been studied using primarily theoretical tools, while the second and third questions have been studied using a variety of both theoretical and empirical methods involving some type of mismatch measure. In this paper I argue that the method of measuring mismatch is a crucial driver of the final results.

Early work on measuring mismatch and its labour market outcomes involved directly asking workers whether they believed they were over- or under-educated; or deriving mismatch measures by comparing workers' different years of education; or asking workers whether they believed they were over or under-skilled (Badillo Amador et al., 2012; Di Pietro and Urwin, 2006; Kampelmann and Rycx, 2012; Mavromaras et al., 2013; McGuinness and Sloane, 2011; Rohrbach-Schmidt and Tiemann, 2011). Work by Mavromaras et al. (2013) shows that measures of over-/under-skill and over-/under-education do not exhibit similar coefficients in reduced form analysis on earnings and thus it is not clear whether different measures of mismatch can be comparable.

[5] Close to the questions of mismatch is the literature on whether the most productive workers work at the most productive firms (e.g. Abowd et al. (1999); Abowd et al. (2004); Mendes et al. (2010)). This line of study relies on using workers' wages and employer-employee linked data as a principal tool to identify identify whether the most productive individuals work at the most productive firms. It is important to note that assortative matching is not necessarily required to for the absence of mismatch. Depending on the production function, it possible that it is optimal to match the least productive worker to the most productive firm. In this paper we focus on the literature answering a different question, namely "Do workers have the right level of education or skills for their job?" and focus on workers' qualifications, rather than wages. The former literature is not directly related to this paper, but is interesting in the context of understanding how the two literatures could be merged: in an ideal world, we could have a dataset that has information on the skills of the workers, the tasks of the job, the wages of the worker, the employer-employee link and the firm's revenue. Having such information would allow us to completely understand what forms a good match between a worker and a job, both in terms of productivity and skills simultaneously.

Figure 1.2: Distribution of Numeracy skills among Graduates and High-School leavers



Recent papers have moved on to multi-dimensional measures of mismatch. Examples include work by Fredriksson et al. (2018), Guvenen et al. (2015), Lise and Postel-Vinay (2016), Pellizzari and Fichen (2017). These papers take the mismatch measure one step further by including different measures for different skills (such as numeracy, literacy and social skills) and by relying on official tests administered by educational or other official bodies. Thus mismatch is not solely a function of years of education or based on a yes-no question asked to the worker.

Perhaps surprisingly, there has been little discussion about why it is better to retire uni-dimensional measures of mismatch for multi-dimensional ones so I will provide the basic arguments here. A commonly used measure of uni-dimensional mismatch is to compare the years of education to others working the same occupation. The problem with years of education is that they are a very noisy measure. As Figure 1.2 shows, having the same level of education by no means translates to having the same level of skills. We see that numeracy skill scores in the PIAAC data not only vary widely within educational categories, but they also overlap between educational categories. The other type of uni-dimensional mismatch measures are the yes-no questions, and the problem with those - which are based on the worker's perception of his own mismatch - is that they are endogenous to the agreeableness of the workplace, the working conditions and, more generally, job satisfaction as shown by Badillo Amador et al. (2012). Furthermore, we completely lose the intensive margin of mismatch, which, as is shown later, significantly matters in the correlation between mismatch and wages.

Overall, we can say that i) self-reported measures of over-/under-education are likely to be biased by third factors and ii) using years of education as a benchmark for mismatch is likely to be misleading due to the large heterogeneity of skills within educational grades.

This paper is also relevant to the task literature, in the context of which economists have argued in favour of making a distinction between workers' human capital and the requirements of the job, in order to provide explanations to phenomena such as job polarisation (Autor et al., 2003) (Goes et al. 2010), earnings differentials (Acemoglu and Autor, 2011; Yamaguchi, 2012) and the closing of the gender wage-gap (Black and Spitz-Oener, 2010; Beaudry and Lewis, 2014) that cannot be explained in the canonical human capital model (Acemoglu and Autor, 2011; Autor, 2013). I extend the task approach to measuring mismatch and highlighting that excluding individual-level tasks from a measure of mismatch will tend to i) under-estimate the extent of mismatch and ii) significantly under-estimate the effect of mismatch on wages.

1.3 Data

I use the 1st round of the Programme for the International Assessment of Adult Competencies (PIAAC), which was conducted between 2008 and 2013 by the Organisation for Economic Cooperation and Development (OECD). The survey was run in 23 OECD countries, however, in this study I only use nine of them for reasons of data availability. The majority of the countries surveyed for PIAAC are missing one or more of the variables required for the current analysis and had to be excluded from the sample [6]. The nine countries used in this study are: Belgium, The Czech Republic, Denmark, France, Italy, The Netherlands, Poland, Slovakia and Spain. I choose to group countries in order to facilitate comparisons and keep enough observations per cluster. The grouping is as follows: Northern Europe includes Flanders(Belgium), Denmark and the Netherlands; Southern Europe includes France, Italy and Spain and Centra Europe includes the Czech Republic, Poland and Slovakia. The dataset contains information on demographic characteristics, earnings, employment history, on-the-job training, occupation categories and so on. Most importantly, however, the innovation of this data is that it contains contemporaneous measures of skills and job-tasks for each individual and these variables are comparable across different countries. PIAAC is a cross-section dataset.

I focus on individuals aged 16-65 years, who are employed full-time, excluding the self-employed. In terms of sample sizes (see Table 1.1), there is some variation between different countries, the smallest sample being from Italy and the largest from Denmark. Northern European countries (Belgium, Denmark and the Netherlands) have the lowest proportion of individuals working full-time, with the Netherlands having only 59% of the population in full-time employment. We control for the above characteristics.

[6] For example, Germany, Estonia, Finland, Ireland and Sweden do not have occupational categories. The US does not have earnings information.

Table 1.1: Summary Statistics

	BEL	CZE	DNK	FRA	ITA	NLD	POL	SVK	ESP
Sample Size	2,721	2,648	4,466	3,681	1,823	3,203	3,930	2,485	2,475
Female	0.48	0.50	0.49	0.48	0.44	0.48	0.43	0.47	0.47
Log of montly earnings (PPP adjusted)	8.01	7.12	8.06	7.67	7.69	7.76	7.01	7.06	7.56
% Full-Time	0.74	0.91	0.82	0.83	0.83	0.59	0.89	0.94	0.82
Age 16-25	0.12	0.16	0.12	0.10	0.07	0.17	0.45	0.11	0.10
Age 26-35	0.24	0.27	0.16	0.22	0.21	0.18	0.23	0.25	0.25
Age 36-45	0.27	0.24	0.23	0.27	0.35	0.24	0.13	0.26	0.23
Age 46-55	0.28	0.19	0.24	0.28	0.26	0.23	0.12	0.26	0.24
Age 56-65	0.10	0.14	0.25	0.14	0.12	0.16	0.07	0.12	0.11
Primary School	0.03	0.00	0.01	0.05	0.04	0.06	0.01	0.00	0.16
Lower Secondary	0.09	0.08	0.17	0.14	0.25	0.20	0.07	0.09	0.24
Upper Secondary	0.41	0.64	0.35	0.44	0.48	0.40	0.55	0.67	0.20
Professional Degree	0.29	0.07	0.24	0.14	0.02	0.04	0.06	0.01	0.12
Bachelor	0.02	0.04	0.08	0.12	0.19	0.21	0.10	0.04	0.13
Master/PhD	0.16	0.18	0.15	0.12	0.03	0.10	0.22	0.20	0.16

[1] 'Full-time' refers to individuals working more than 35 hours a week.
[2] We use monthly earnings, since hourly wages had a large number of missing values.
[3] The sample includes employed individuals only (no self-employed).

1.4 A measure of multi-dimensional mismatch: skill-task Mismatch

In this section I introduce the skills and tasks measures available in the PIAAC dataset and upon which I construct a measure of mismatch to compare male versus female mismatch. The major advantage of this particular dataset is that for both numeracy and literacy we have information not only on the individual's skill level in that particular dimension but also on the frequency with which they do tasks that use those particular skills. It is not yet a standard practice in the literature to study mismatch by comparing one's skill level to one's use of the tasks that use that skill the most, relative to others in similar occupations. In other datasets that have been used to study mismatch, we either only have the skills information (e.g. Swedish administrative data in Fredriksson et al. (2018)) or we can have both but with the tasks not being at the individual level (e.g. the American NLSY in Guvenen et al. (2015)). PIAAC combines detailed information on both skills and tasks, at the individual level, allowing for a definition of mismatch that incorporates the assumption that the more able workers in a given dimension (e.g. literacy) should be expected to do more of the tasks using the skill in which they have a comparative advantage, an assumption that cannot be exploited when either the skills or the tasks at the individual level are missing. PIAAC also contains information on manual, social and problem solving tasks, however I do not include these in the current analysis due to i) the lack of corresponding skill information on manual and social skills and ii) the large number of missing observations for the tests on problem solving skills.

1.4.1 Skills measures in PIAAC

Respondents in the PIAAC survey are tested in two main skills: literacy and numeracy. The test materials are made up of a battery of 114 standardised test questions (58 literacy and 56 numeracy items), examples of which can be seen in Appendix B. The respondents do not answer all 114 questions - the test is designed to be attributed in stages. In the first stage, respondents answer three easy literacy and numeracy questions, to determine whether they should continue with the assessment. If they pass, respondents are then randomly assigned to take a literacy, numeracy or problem solving test consisting of 9 questions in the first round, before being randomly re-assigned to take a second round of questions in either of the topics they haven't taken, now consisting of 11 questions. The literacy and numeracy assessments are offered in the country's local language and have an adaptive design, i.e.

respondents are directed to different blocks of items based on their estimated ability (OECD (2013)).[7] The test scores range from 0 to 500 and are calculated following the principles of Item Response Theory (ITM), where the answers of all respondents in all countries are used to estimate a model that produces a skill proficiency measure for each participant. This method of deriving skills measures affects the way in which the data has to be subsequently used: all statistics and estimations for the skills scores have to be calculated using jackknife standard errors (OECD (2013)).[8]

Tables 1.3 - 1.4 provide a set of summary statistics for the skills scores. Table 1.2 shows the average skills scores by region, gender and education. On average Northern European countries have higher scores in both literacy and numeracy, across all categories relative to Southern and Eastern Europe. As expected, we clearly see that skills scores increase with education and we also see that men will score much higher than women in numeracy, but only in Northern Europe. The literacy scores are very similar for both sexes. Table 1.4 shows the scores for the 5 quantiles of the distribution. Southern Europe's scores appear to be much lower than the rest of Europe at nearly all points of the distribution. The result is not driven by one particular country: we can see in Table 1.3 that the average skill level in the three Southern European countries is lower than both Northern and Eastern Europe.

Although the skills measures were obtained for problem solving, in addition to numeracy and literacy, I will not be using them. Up to 30% of the respondents per country have not taken the problem solving test, which leads to worries of sample selection. All respondents have taken both the numeracy and literacy tests.

[7] Around 23% of the sample averaged across all participating countries (i.e. taking into account countries not included in this study) took a paper-based assessment, instead of a computer-based one. These were people who either failed to pass a basic ICT skills test at the beginning of the assessment or who chose to take the test with pen and paper, despite being computer literate. The structure of the test is different for this group: in the first stage they complete 4 literacy and 4 numeracy questions. In the second stage, they are randomly assigned to complete 20 questions in either literacy or numeracy and subsequently everyone completes a reading component.

[8] In addition to literacy and numeracy, skills measures were obtained for problem solving too. I will not be using the problem solving tests since up to 30% of the respondents per country have not taken the problem solving test, which leads to worries of sample selection. All respondents have taken both the numeracy and literacy tests.

Table 1.2: Average skill scores by region, gender and education

	Northern Europe	**Southern Europe**	**Eastern Europe**
Literacy	287	262	274
Numeracy	287	259	271
Female			
Literacy	286	261	277
Numeracy	281	262	270
Male			
Literacy	287	263	272
Numeracy	293	255	272
Degree			
Literacy	309	290	299
Numeracy	310	290	295
High-School Diploma			
Literacy	283	262	265
Numeracy	283	259	264
Less than High-School			
Literacy	257	232	242
Numeracy	255	226	232

The maximum score is 500. Scores are weighted using country weights provided by PIAAC. Northern Europe includes Flanders, Denmark and The Netherlands; Southern Europe includes France, Italy and Spain; and Eastern Europe includes Czechia, Poland and Slovakia.

1.4.2 Task measures in PIAAC

The survey contains information on different types of tasks encompassing cognitive skills, technology, interaction with others, learning, organisation and physical work. Since we only have test information on the cognitive skills of individuals, in order to measure mismatch we focus on cognitive tasks only. The cognitive job tasks are categorised in two dimensions: numeracy and literacy (reading and writing) and can be seen in table 1.5 (OECD (2013)). Individuals self-report whether they undertake

Table 1.3: Average skill scores by country

	Belgium	Czech Republic	Denmark	France	Italy	The Netherlands
Numeracy	287	280	286	261	255	287
Literacy	281	277	277	266	255	290
	Poland	**Slovakia**	**Spain**			
Numeracy	267	285	256			
Literacy	272	280	260			

The maximum score is 500. Scores are weighted using country weights provided by PIAAC.

Table 1.4: Quantiles of skills score by region

	q1	q2	q3	q4	q5
Northern Europe					
Literacy	220	267	291	312	344
Numeracy	225	270	291	310	337
Southern Europe					
Literacy	193	240	265	288	322
Numeracy	193	238	263	284	314
Eastern Europe					
Literacy	211	253	277	298	333
Numeracy	215	253	273	294	320

The maximum score is 500. Scores are weighted using country weights provided by PIAAC. Northern Europe includes Flanders, Denmark and The Netherlands; Southern Europe includes France, Italy and Spain; and Eastern Europe includes Czechia, Poland and Slovakia.

the tasks in their current job. Each of the tasks varies in intensity within a score of 0-5, where 0 means "I never do the task" and 5 means "I do the task everyday".

Table 1.6 shows the average task intensity in the two dimensions, and for each region. Like with the average literacy skills by region, we see that task intensity in literacy is highest in Northern Europe. However, unlike the average numeracy skills scores in table 1.2, we see that task intensity in numeracy is more equally distributed among the different regions here. The lower variation in task intensity may be an outcome of the numeracy tasks being fewer in their number, relative to literacy tasks. The 2nd and 3rd panels show the task intensity by gender. The numbers are relatively, with the exception of numeracy in Northern Europe: men appear to have much more numeracy-intensive work than women. In terms of education, we see that the intensity of task use increases with the level of education, as would be expected. The difference between the most and least educated are starkest in Eastern Europe.

Table 1.5: Literacy and Numeracy Tasks

Literacy tasks	**Numeracy tasks**
read directions or instructions	calculating costs or budgets
read letters, memos or e-mails	use or calculate fractions or percentages
read newspapers or magazines	use a calculator
read professional journals or publications	prepare graphs, charts or tables
read books	use simple algebra or formulas
read manuals or reference materials	use advanced math or statistics
read financial statements	
read diagrams, maps or schematics	
write letters	
write articles	
write reports	
fill in forms	

The dataset also contains manual, social and problem solving tasks. I do not include those in the analysis due to the lack of corresponding tests on manual and social skills.

Table 1.6: Average task scores by region, gender and education

	Northern Europe	**Southern Europe**	**Eastern Europe**
Literacy	32.7	28.8	28.5
Numeracy	13.0	12.7	13.9
Female			
Literacy	32.1	28.3	29.0
Numeracy	11.8	12.3	14.3
Male			
Literacy	33.3	29.4	28.1
Numeracy	14.2	13.1	13.5
Degree			
Literacy	37.8	35.9	36.4
Numeracy	15.2	15.8	16.8
High-School Diploma			
Literacy	30.9	28.0	26.5
Numeracy	12.2	12.4	13.1
Less than High-School			
Literacy	25.3	20.8	18.9
Numeracy	9.9	9.2	9.8

The maximum task intensity score for literacy is 60 and for numeracy 30. These intensity scores are calculated by adding up the task scores (0 to 5) for each literacy and each numeracy task. Northern Europe includes Flanders, Denmark and The Netherlands; Southern Europe includes France, Italy and Spain; and Eastern Europe includes Czechia, Poland and Slovakia.

1.4.3 The measure of Skill-Task Mismatch

Every individual has a skill score ranging from 0 to 500, in each of the two skills measures. This means that it is possible to create two separate skill score rankings of individuals or, in other words, create two skill score distributions: one for numeracy and one for literacy. Subsequently, I create two juxtaposing distributions based on how intensively the individual uses each type of job-task: numeracy- and literacy-intensive job tasks. For each task, every individual gets a score from 0 to 5 based on how intensively they do that job task. I add the job-task scores by knowledge dimension, which then gives me two job-task intensity distributions: one for numeracy and one for literacy [9].

Every individual has a skill score ranging from 0 to 500, in each of the numeracy and literacy skills measures. This means that it is possible to create two separate skill score rankings normalised between 0 and 1: one for numeracy and one for literacy. Subsequently, we can create a similar ranking based on how intensively the individual uses each dimension of job-task, i.e. numeracy and literacy. For each task, every individual gets a score from 0 to 5 based on how intensively they do that job task. Adding the job-task scores by dimension (literacy or numeracy), gives us two job-task intensity rankings: one for numeracy and one for literacy.[10] For numeracy, the highest possible numeracy task score is 30, referring to someone who does all numeracy tasks everyday.[11] For literacy, the highest score is 60 respectively. To allow for comparison between the skill rank and the task rank we normalise the task ranking between 0 and 1. Thus an individual can have have a literacy task rank of 0.46 and a literacy skill score of 0.35.

Once the four distributions have been computed (i.e. one skill score distribution and one job-task intensity distribution for each of numeracy and literacy), the skill-task measure of mismatch consists of comparing one's position in the skill distribution to their position in the task distribution. Thus, using the previous example, if someone has a literacy skill score rank of 0.35 and a literacy task rank of 0.46 it means that 34% of of the sample has a lower literacy score than him/her and 65% of the sample has a higher literacy score. Similarly, for the literacy rank, the interpretation is that 45% of the sample has a job with lower literacy task intensity and 55% of the sample has a job with higher literacy task intensity. The indvidual

[9]Note that each job-task is weighted equally.

[10]Note that each job-task is weighted equally.

[11]Since there are are 6 numeracy tasks in total and the highest intensity score for each task is '5' (everyday), the maximum score is for numeracy job-task intensity is 5*6=30.

in question is slightly mismatched in one of two ways: they would be 'under-skilled' in the sense that given their position in the task distribution they have too little skill compared to their peers; or they would be 'over-tasked' in the sense that given their position in the skill distribution, they are doing too much of the tasks that best suit their lower level of literacy skill. If it is zero, it means that the individual's position in the task ranking is exactly the same at their position in the skill score ranking.

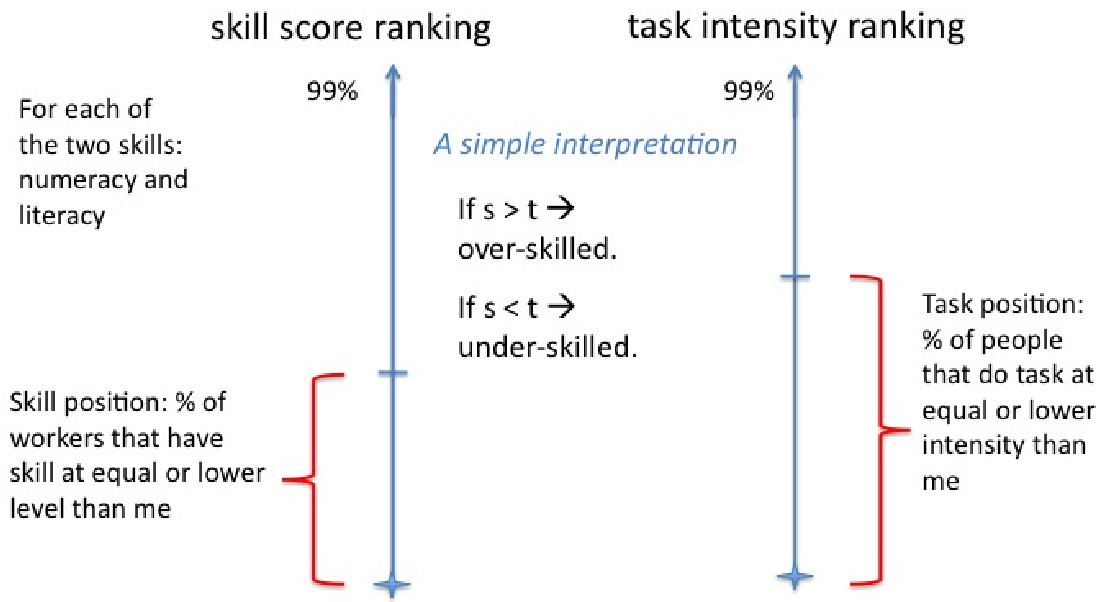


Figure 1.3: Graphical Representation of Skill-Task Mismatch

The simplest way to obtain a measure of mismatch from the comparison of the the task and skill rankings is by subtracting each individual's position on the task distribution from their position on the skill distribution:

$$\text{Mismatch}_i \quad = \quad \text{Skill Position}_i - \text{Task Position}_i,$$

where the units of Mismatch are percentage point differences between the skill distribution and the task distribution. If $Mismatch_i$ is positive then the individual is over-skilled (or under-tasked) and if it is negative then the individual is under-skilled (over-tasked). Since the measure is continuous, we do not observe any perfect zeros in the data. Figure 1.3 provides an illustration of how the skill-task mismatch is interpreted.

It is worth noting that this measure takes on both positive and negative values, meaning that in a Mincer regression a unit increase will be interpreted as a decrease in mismatch if it is on the negative side of the measure, but as an increase in mismatch if it is on the positive side. Given previous studies on the differential effects of being over-skilled versus being under-skilled on wages, it is not expected that the absolute value of the partial effect will be the same along the positive and negative side of the distribution.

1.5 Who is mismatched?

Figures 1.4-1.6 provide an overall picture of how much mismatch there is in each region and each skill. Since the measure of Skill-Task mismatch is a relative measure, the results we observe are dependent on who we choose to add in the sample. If we chose to group countries differently, the shape of the distributions will change - in the following examples, we adopt the regional grouping that is used throughout this paper, i.e. we split the sample into Northern, Southern and Eastern Europe. Given that this measure is continuous, we can see that everyone is, to some extent, mismatched. Nevertheless, the bulk of observations in all regions is concentrated around 0, which shows that most people are not highly mismatched. Across regions, however, we see some clear differences in how the mismatch is distributed.

In literacy, Southern European countries, consisting of France, Italy and Spain, have a relatively bell-shaped distribution, while in Northern (Belgium, Denmark and The Netherlands) and Eastern Europe (Czechia, Poland and Slovakia) the curve is skewed to the right (right panel of Figures 1.4-1.6). We can interpret the different distribution shapes as a suggestion that literacy mismatch is primarily a problem of being over-skilled rather than under-skilled in Northern and Central Europe. Looking at the magnitudes of literacy mismatch we see that 11-15% of the sample are mismatched in Northern and Central Europe, and 10% in Southern Europe.[12] These percentages are not by country, but for the region in question. For numeracy (left panel of Figures 1.4-1.6), we observe that the mismatch distribution is skewed to the right for Northern and Central Europe and slightly less so in Southern Europe. We see that 18-24% of the population is mismatched in Central and Northern Europe respectively, while 14% is mismatched in Southern Europe.

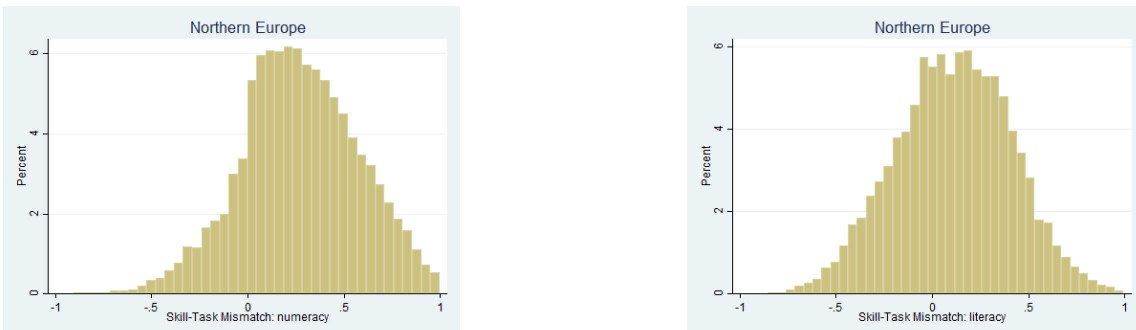


Figure 1.4: Northern Europe: Numeracy & Literacy Mismatch

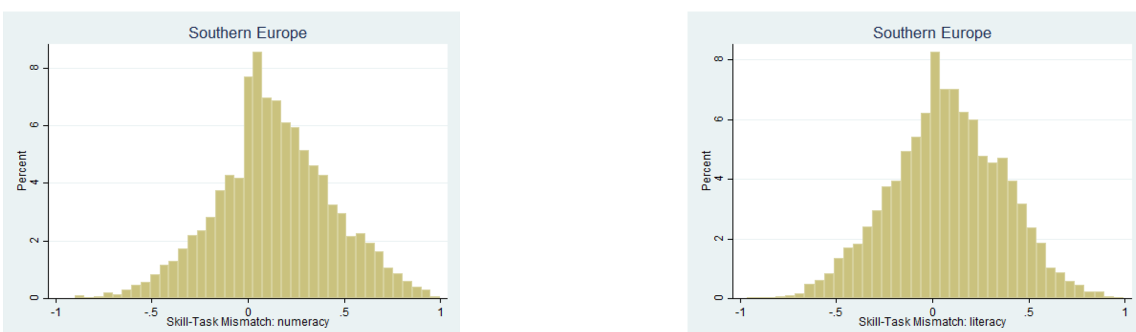
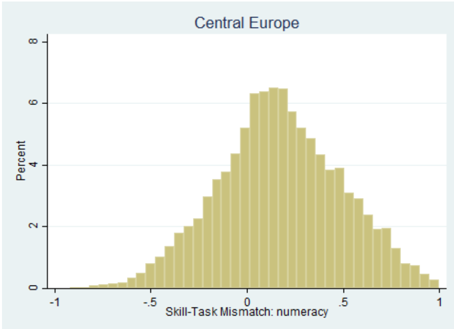


Figure 1.5: Southern Europe: Numeracy & Literacy Mismatch

[12]To simplify the comparison between the three measures, I am going to compare the densities for the three measures for a value of mismatch that is higher than 0.5 (strongly over-skilled) or lower than -0.5 (strongly under-skilled).



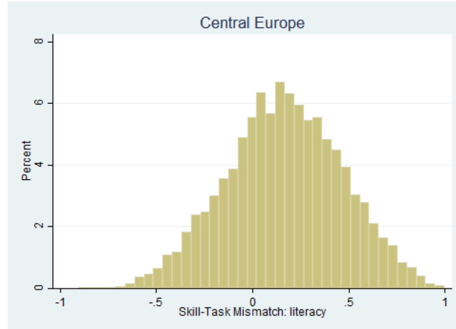


Figure 1.6: Central Europe: Numeracy & Literacy Mismatch

1.6 Multi-Dimensional Mismatch and Wages: the baseline results

In what follows, I use skill-task mismatch to study how it compares to other studies of mismatch in its correlation with wages. The basic empirical model can be written as follows:

$$lnw_i \;=\; \beta_1|Mismatch_i| + \beta_2 Mismatch_i^2 + \gamma_1 Skill_i + \gamma_1 Task_i + X_i\beta + \alpha_{ki}OCC_{ki} + v_i$$

The dependent variable is the log of monthly PPP-adjusted earnings. The subscript i stands for individuals and k for occupations. The first two independent variables $|\text{Mismatch}_i|$ and Mismatch_i^2 are the two variables of interest. The "Skill" variable is the skill score in either Numeracy or Literacy and the "Task" variable is the task intensity scores in Numeracy or Literacy. The model is run separately for numeracy and literacy. Included are a number of demographic controls like gender, age, age squared, hours worked and education, as well as occupational categories.

Table 1.7 lists the results of the correlation between overall mismatch and wages. For most countries, the contemporaneous correlation between mismatch and wages is not significant, either between or within occupations. It is perhaps surprising that only Northern European countries showcase a negative effect of mismatch on wages. Other studies which use multi-dimensional measures of mismatch have found significant and negative correlations between mismatch and wages. These have been analysed for the US (Guvenen et al 2015; Lise et al 2015) and Sweden (Hendrikkson 2014) which have similar macroeconomic characteristics to the Northern European countries included here (Flanders, Denmark and The Netherlands). Nevertheless, the studies for the US abd Sweden have used longitudinal data, in which the level of mismatch of an individual is monitored throughout life. There are currently no studies of multi-dimensional mismatch for Southern and Eastern European countries, so we do not have a direct benchmark of comparison.

For Northern Europe, there is a strong, negative and non-linear correlation between mismatch and wages which persists within occupations. The negative effect of the mismatch is particularly pronounced for individuals at the extreme tails of the distribution, so that low levels of mismatch are not significant(see column (2) of Table 1.7). Overall, at most 20% of the negative correlation can be explained by occupational fixed effects (column (3) of Table 1.7). In fact, the significant negative correlation for Northern Europe appears to go above and beyond occupational fixed effects, education, gender and age controls. In the rest of the geographical areas, we do not observe a situation where the mismatch effect disappears as soon as we add the occupational fixed effects. In the only geographical area in which there is a negative and significant mismatch effect, it persists even after occupational effects.

In all of the countries, the absolute effect of the skill level and the task intensity are positive and statistically significant, both between and within occupations. In other words, holding all else equal, a unit increase in the skill score, increases wages by around 0.1%. Similarly, a unit increase in the task intensity score increases wages on average 50% for literacy and 18% for numeracy. While the mismatch variables capture the effect of one's relative position in the skill-task distribution compared to everyone else within their occupation, controlling for the absolute level of their skill level and task intensity allows us to whether being better in certain skills or tasks appear to have higher return overall.

Table 1.7: Effect of Skill Level, Task Intensity and Skill-Task Mismatch on Wages

	Northern Europe			Southern Europe			Eastern Europe		
	(1)	(2)	(3)	(4)	(5)	(6)	7	(8)	(9)
Literacy									
$\lvert Mismatch \rvert$	-0.140**	0.189	0.168	-0.052	0.105	0.106	-0.042	0.167	0.177
	(0.056)	(0.142)	(0.135)	(0.035)	(0.126)	(0.118)	(0.052)	(0.147)	(0.141)
$Mismatch^2$	-	-0.500***	-0.443**	-	-0.247	-0.232	-	-0.313	-0.305
		(0.188)	(0.178)		(0.201)	(0.195)		(0.212)	(0.204)
Tasks	0.636***	0.602***	0.433***	0.747***	0.738***	0.514***	0.787***	0.770***	0.625***
	(0.056)	(0.056)	(0.057)	(0.036)	(0.035)	(0.041)	(0.060)	(0.061)	(0.070)
Skills	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Occupations	-	-	✓	-	-	✓	-	-	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓	✓
Education	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓	✓	✓	✓
Numeracy									
$\lvert Mismatch \rvert$	-0.071	0.057	0.015	0.023	0.057	-0.026	-0.010	-0.118	-0.096
	(0.055)	(0.115)	(0.116)	(0.036)	(0.115)	(0.102)	(0.049)	(0.138)	(0.139)
$Mismatch^2$	-	-0.159	-0.135	-	-0.159	0.038	-	0.151	0.135
		(0.124)	(0.125)		(0.124)	(0.102)		(0.175)	(0.176)
Tasks	0.230***	0.224***	0.134**	0.304***	0.224***	0.133***	0.419***	0.425***	0.334***
	(0.060)	(0.061)	(0.063)	(0.030)	(0.061)	(0.031)	(0.050)	(0.050)	(0.047)
Skills	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Occupations	-	-	✓	-	-	✓	-	-	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓	✓
Education	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓	✓	✓	✓

Each column and skill is a separate regression, i.e. there are a total of 18 different regressions. The dependent variable is the log of ppp-adjusted monthly earnings. The demographic controls include age, age squared, gender, native speaker and hours worked. The education controls include a total of 5 levels of education, from primary to master's degree. Country dummies are also included, and vary by regoin. Northern Europe has dummies for Flanders, the Netherlands and Denmark; Southern Europe for France, Italy and Spain and Eastern Europe for Czech Republic, Poland and Slovakia. In columns (3), (6) and (9) of each set, 267 3-digit occupational controls are included.

1.7 Multi-dimensional measures of mismatch in the literature

While several papers in the literature have proposed measures of multi-dimensional mismatch ((Pellizzari and Fichen, 2017); (Fredriksson et al., 2018); (Guvenen et al., 2015); (Lise and Postel-Vinay, 2016)), there have been no systematic comparisons between the different measures. In this section I compare the new measure I propose with the one proposed by (Pellizzari and Fichen, 2017), which does not use tasks and the one by proposed by Guvenen et al. (2015), in which tasks are aggregated at the occupational level [13]

1.7.1 Comparison with the OECD measure of mismatch

The multi-dimensional mismatch measure by (Pellizzari and Fichen, 2017) can be summarised as follows: for the two skill domains (literacy and numeracy) minimum and maximum requirements are defined as the minimum and maximum proficiency of self-reported well-matched workers.[14] Thus, workers are classified as 'well-matched' if their score in that domain is between the minimum and maximum score observed for workers that report to be well-matched. The minimum and maximum thresholds are derived separately by 1-digit occupation and by country. Figure 1.7 provides an illustration of the mechanism.

In Pellizzari and Fichen (2017), the authors create a different measure of mismatch using the same dataset as this paper, i.e. PIAAC. Their measure defines three categories of workers: the well-matched, the over-skilled and the under-skilled. The well-matched are those workers who report to be well- matched within a 1-digit occu-

[13]The measure used by Fredriksson et al. (2018) is similar to that of Pellizzari and Fichen (2017) in that it only uses skills. Unfortunately, due to the cross-section nature of PIAAC, I am not able to replicate the mismatch measure by Fredriksson et al. (2018), because it requires information on the job movements of workers. The measure used by Lise and Postel-Vinay (2016) is the same as that by Guvenen et al. (2015).

[14]The self-reported well-matched workers are those that report not to "have the skills to cope with more demanding duties than those they are required to perform in their current job" as well as not having the "need for further training in order to cope with their present duties".

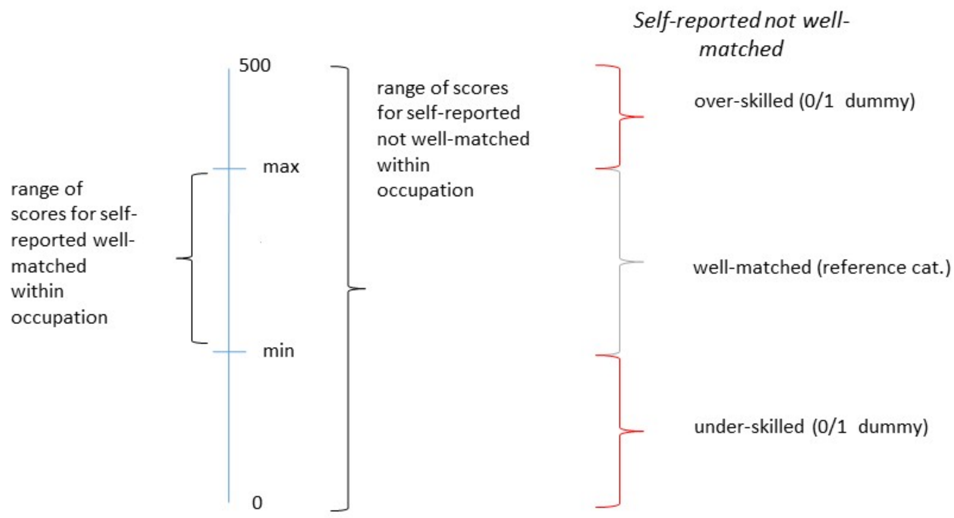


Figure 1.7: Illustration of the Pellizzari and Fichen (2017) measure of Mismatch.

pation. The over-skilled are those workers whose skills scores are above those of the well-matched within the same occupation. The under-skilled are the workers whose skills scores are below the scores of the well-matched, again in the same occupation. Thus in a regression set-up, two out of the three categorical dummies are included, the reference category being the well-matched.

The first comment we can make is that the Pellizzari and Fichen (2017) measure, by construction, does not take into account the intensive margin of mismatch which, as shown in Table 1.7, matters for wages. To closely compare the Skill-Task mismatch measure and the F&P measure in a Mincer equation, I re-formulate the Skill-Task Mismatch measure in three categories of over-, under- and well-matched. I set the well-matched scores to be between -0.20 and 0.20 and create three dummy categories. I also replicate the F&P measure here and test how it fares in the basic Mincer

Table 1.8: Comparison: Skill-Task Mismatch versus Fichen & Pelizzari (2013)

	Northern Europe		Southern Europe		Eastern Europe	
	This paper	F&P 2013	This paper	F&P 2013	This paper	F&P 2013
Literacy						
Over-skilled	0.044	-0.006	0.010	-0.013	0.011	0.007
	(0.032)	(0.068)	(0.027)	(0.041)	(0.042)	(0.044)
Under-skilled	-0.131***	-0.012	0.003	0.014	-0.033	0.011
	(0.038)	(0.061)	(0.026)	(0.033)	(0.052)	(0.049)
Numeracy						
Over-skilled	-0.005	-0.026	-0.009	0.026	-0.001	0.012
	(0.030)	(0.065)	(0.023)	(0.034)	(0.040)	(0.045)
Under-skilled	-0.101**	0.002	0.002	-0.004	-0.012	0.04
	(0.049)	(0.040)	(0.029)	(0.030)	(0.038)	(0.045)
1-digit OCC	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Education	✓	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓

Each column is a separate regression. The first column of each set shows the coefficients from the correlation between wages and Skill-Task Mismatch measure. The second column shows the coefficients from using the measure defined by Fichen & Pelizzari (2013). The dependent variable is the log of ppp-adjusted monthly earnings. The demographic controls include age, age squared, gender and native speaker and hours worked. The education controls include a total of 5 levels of education, from primary to master's degree. Levels of skills scores and task intensities are also controlled for. Country dummies are also included. To closely match the analysis of Pellizzari and Fichen (2017), I only control for 1-digit occupation dummies.

equation set-up compared to the skill-task mismatch measure.

The results of this comparison can be found in Table 1.8. The take-away from the comparison is that the two measures do not measure the same thing in all countries. In Northern European countries, the Skill-Task mismatch measure picks up negative effects of being under-skilled that are not present when using the F&P measure, which is only based on skills. Moreover, the F&P measure does not pick up any effects that are not already picked up by the Skill-Task Mismatch measure, which suggests that F&P will be only under-estimating the effects of mismatch on earnings.

1.7.2 Comparison with Guvenen et al. 2015 measure of mismatch

A growing theoretical literature has been using the NLSY/O*NET data to create measures of mismatch using skills tests and occupational tasks (Guvenen et al. (2015); Lise and Postel-Vinay (2016); Lindenlaub (2017)).

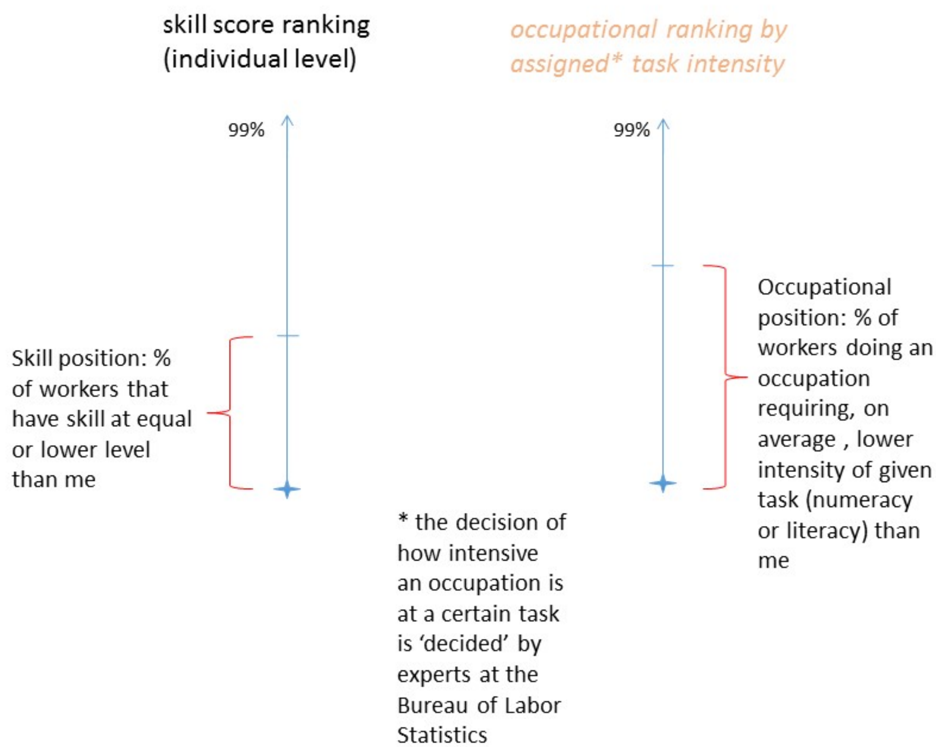


Figure 1.8: Diagram of Guvenen et al. (2015) measure of Mismatch

The mismatch measure used in NLSY/O*NET-based work and in Guvenen et al. (2015) involves comparing each individual's relative skill level with the required relative skill level of his/her occupation. Such a comparison is made possible in the following way: individuals in the NLSY take different aptitude tests in numeracy, literacy and social skills. The availability of scores for these tests means that individuals can be ranked according to their test score and thus we can obtain an ability distribution for each skill. At the same time occupations can also be ranked by the expected skill-use intensity. So, each occupation can be ranked according to how intensively it requires numeracy, literacy or social skills. Subsequently, we can take the difference between an individual's position in the given skill distribution with his/her occupation's position in the given skill requirement distribution. The idea is that the individual's relative position in the distribution should mirror the relative position of his/her occupation, in terms of how intensively the given skill is used. The mechanism of the NLSY-based measure is illustrated in Figure 1.8

The mismatch measure used in NLSY/O*NET-based work is very similar to the one proposed here. The main difference lies in how the differences in task intensity are accounted for. In PIAAC, given that we have task intensity information at the individual level, it is possible to create a task intensity distribution at the individual level, where being higher up in the distribution means performing a type of task more intensively. In NLSY/O*NET, task intensity information is available only at the occupational level and thus it is occupations - rather than individuals - that are ranked based on how intensively a task in performed in a given occupation. Thus, for the set of individuals that are observed to be in the same occupation, it is assumed that they all perform certain tasks at an identical level of intensity. Thus while in PIAAC we can observe task variation at the individual level, in the NLSY/O*NET we can only observe task intensity variation between occupations only.

Not being able to observe individual-level variation in task-intensity may not be a problem, if it weren't for the fact that individual task bundles are significantly different even within narrowly defined occupations as shown in (Autor and Handel, 2013). Figure 1.1 in the introduction shows that one can still observe significant differences in daily tasks within narrowly defined occupations.

To make a direct comparison between the Skill-Task Mismatch measure and the (Guvenen et al., 2015) measure possible, I construct the over- and under-skilled categories from my own measure to match the structure of theirs. More specifically,

Table 1.9: Comparison: Skill-Task Mismatch versus NLSY measure by Guvenen et al. (2015)

	Northern Europe		Southern Europe		Eastern Europe	
	This paper	Guvenen et al 2015	This paper	Guvenen et al 2015	This paper	Guvenen et al 2015
Literacy						
Over-skilled	0.160	-0.162***	0.225***	0.010	0.119	-0.112
	(0.101)	(0.054)	(0.074)	(0.057)	(0.210)	(0.107)
Under-skilled	0.317***	0.040	0.257***	0.018	0.111	-0.137
	(0.116)	(0.090)	(0.089)	(0.050)	(0.226)	(0.115)
Numeracy						
Over-skilled	0.113	0.002	0.195***	-0.046	-0.139	-0.010
	(0.097)	(0.043)	(0.079)	(0.038)	(0.115)	(0.009)
Under-skilled	0.255**	0.009*	0.232***	0.021	-0.206	0.003
	(0.127)	(0.050)	(0.090)	(0.033)	(0.164)	(0.073)
3-digit OCC	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓
Education	✓	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓
Experience	✓	✓	✓	✓	✓	✓

Each column is a separate regression. The first column of each set shows the coefficients from the correlation between wages and Skill-Task Mismatch measure. The second column shows the coefficients from using the measure defined by Guvenen et al. (2015). The dependent variable is the log of ppp-adjusted monthly earnings. To closely follow the Guvenen et al. (2015) setup, in each of the estimations I control for female, experience, experience squared, experience cubed, employer tenure, employer tenure squared, native speaker, as well as hours worked since I only have access to monthly earnings. The education controls are: less than high school, high school and degree and the level of skills and task intensities. I include 3-digit occupation dummies.

unlike in the (Pellizzari and Fichen, 2017) where there is three groups (well-matched, over-skilled and under-skilled) there are only 2 groups here: the over-skilled, where we have a variable equal to zero if the individual has a zero *or* a negative value for the mismatch measure and is equal to the mismatch value if it is greater than zero; and the under-skilled, which takes a value of zero for those with zero *or* positive mismatch, and takes the observed negative value for those with negative mismatch. I include these two categories in a Mincer type regression, and I use the exact same controls as they Guvenen et al. (2015).

The results are shown in tables 1.9. We see that in both Northern and Southern Europe, the (Guvenen et al., 2015) measure will tend to under-estimate the effect of mismatch on wages, in particular the effect of being under-skilled. For Southern

Europe, we observe a set of unusual results for the Skill-Task Mismatch, relative to what we have seen so far (no significant effects): these are due to following the unusual formulation of the over- and under-skilled groups, where each is compared not to the well-matched but to part of the well-matched and all the mismatched on the other side of the distribution. Unline with the F&P measure, we see that the Guvenen et al. (2015) measure picks effects that are not present in any of the other measures, specifically for Northern Europe. Nevertheless, the comparison is not quite perfect since I cannot directly replicate the resutls from Guvenen et al. (2015) for lack of US data. In the best possible scenario I would be able to test these two measures on a US sample - which is what Guvenen et al. base their analysis - but US wage data is not available in PIAAC.

1.8 Conclusion

In this paper I have used a dataset of OECD countries to study mismatch in the labour market and have created a mismatch measure that could not be obtained from previous datasets. I find that extreme levels of skill-task mismatch negatively correlate with wages in some EU countries. I then compare the Skill-Task Mismatch measure with other measures of multi-dimensional mismatch that use less rich data. I find that measures with higher levels of aggregation or measures that exclude tasks will tend to under-estimate the effect of mismatch on wages.

Bibliography

Abowd, J. M., F. Kramarz, P. Lengermann, and S. Pérez-Duarte (2004): "Are good workers employed by good firms? A test of a simple assortative matching model for France and the United States," *Unpublished Manuscript*.

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999): "High Wage Workers and High Wage Firms," *Econometrica*, 67, 251–333.

Acemoglu, D. and D. H. Autor (2011): "Skills, tasks and technologies: Implications for employment and earnings," *Handbook of labor economics*, 4, 1043–1171.

Autor, D. H. (2013): "The "task approach" to labor markets: an overview," *Journal for Labour Market Research*, 46, 185–199.

Autor, D. H. and M. J. Handel (2013): "Putting Tasks to the Test: Human Capital, Job Tasks, and Wages," *Journal of Labor Economics*, 31, S59–S96.

Autor, D. H., F. Levy, and R. J. Murnane (2003): "The skill content of recent technological change: An empirical exploration," *The Quarterly Journal of Economics*, 118, 1279–1333.

Badillo Amador, L., Á. López Nicolás, and L. E. Vila (2012): "The consequences on job satisfaction of job–worker educational and skill mismatches in the Spanish labour market: a panel analysis," *Applied Economics Letters*, 19, 319–324.

Beaudry, P. and E. Lewis (2014): "Do Male-Female Wage Differentials Reflect Differences in the Return to Skill? Cross-City Evidence from 1980 to 2000," *American Economic Journal: Applied Economics*, 6, 178–194.

Black, S. E. and A. Spitz-Oener (2010): "Explaining women's success: technological change and the skill content of women's work," *The Review of Economics and Statistics*, 92, 187–194.

Di Pietro, G. and P. Urwin (2006): "Education and skills mismatch in the Italian graduate labour market," *Applied Economics*, 38, 79–93.

Fredriksson, P., L. Hensvik, and O. N. Skans (2018): "Mismatch of talent: Evidence on match quality, entry wages, and job mobility," *American Economic Review*, 108, 3303–38.

Guvenen, F., B. Kuruscu, S. Tanaka, and D. Wiczer (2015): "Multidimensional Skill Mismatch," *NBER Working Paper 21376.*

Kampelmann, S. and F. Rycx (2012): "The impact of educational mismatch on firm productivity: Evidence from linked panel data," *Economics of Education Review*, 31, 918–931.

Lindenlaub, I. (2017): "Sorting multidimensional types: Theory and application," *The Review of Economic Studies*, 84, 718–789.

Lise, J., C. Meghir, and J.-M. Robin (2013): "Mismatch , Sorting and Wage Dynamics," .

Lise, J. and F. Postel-Vinay (2016): "Multidimensional Skills, Sorting, and Human Capital Accumulation," *Manuscript, University of Minnesota.*

Mavromaras, K., S. McGuinness, N. O'Leary, P. Sloane, and Z. Wei (2013): "Job mismatches and labour market outcomes: panel evidence on university graduates." *Economic Record*, 89, 382–395.

McGuinness, S. and P. J. Sloane (2011): "Labour market mismatch among UK graduates: An analysis using REFLEX data," *Economics of Education Review*, 30, 130–145.

Mendes, R., G. J. Van Den Berg, and M. Lindeboom (2010): "An empirical assessment of assortative matching in the labor market," *Labour Economics*, 17, 919–929.

OECD (2013): *The survey of adult skills: Reader's companion*, OECD Publishing.

Pellizzari, M. and A. Fichen (2017): "A new measure of skill mismatch: theory and evidence from PIAAC," *IZA Journal of Labor Economics*, 6, 1.

Rohrbach-Schmidt, D. and M. Tiemann (2011): "Mismatching and job tasks in Germany - rising over-qualification through polarization?" *Empirical research in vocational education and training*, 3, 39–53.

Yamaguchi, S. (2012): "Tasks and Heterogeneous Human Capital," *Journal of Labor Economics*, 30, 1–53.

Chapter 2

Multi-dimensional Mismatch & Gender

2.1 Introduction

The recent availability of skill and task data at the individual level has allowed us to study mismatch from multiple dimensions and to highlight its negative effects on income, both contemporaneously and over the life cycle.[1] However, studies up to now have only been made available for male samples. The omission has been one of chance rather than design, since the type of cognitive tests that are used in multi-dimensional measures of mismatch are the result of military aptitude tests taken by men of conscription age. In this paper, and with the help of new data on female skills, I provide a new set of stylised facts about male versus female mismatch. Studying the differences in mismatch between the female and male population is interesting in and of itself, but it is also important in the context of the gender earnings gap, the majority of which is to be found among individuals doing identical occupations.[2] Using skills and tasks data at the individual level for both men and women can help us shed further light as to the importance of mismatch in explaining earnings gaps

[1] See for example Guvenen et al. (2015); Fredriksson et al. (2018); Lise and Postel-Vinay (2015).
[2] See for example Goldin (2014); Cobb-Clark and Tan (2011).

within occupations.

Using a measure of mismatch developed in chapter 1, which I call skill-task mismatch and which is defined by comparing individuals' position in the skill distribution to their position in the task intensity distribution, I show that mismatch along different dimensions differs for the two genders. I use the Programme for the International Assessment of Adult Competencies dataset (henceforth PIAAC), the only currently available data to offer both skill and daily task information for both genders. The survey is administered by the Organisation for Economic Cooperation and Development (OECD) and measures adults' proficiency in key cognitive skills - literacy, numeracy and problem-solving in technology-rich environments. The survey also provides information on how adults use those skills at work. PIAAC allows me to take advantage of two different dimensions of mismatch, namely in literacy and numeracy. Comparing the levels of mismatch between men and women, I find that it is similar only in literacy. In numeracy, Northern European women tend to have higher skills than would be required for the job, while the men tend to have lower skills than those required. The opposite is true for Southern and Eastern Europe, although at a weaker level than Northern Europe.

Subsequently, I test the consequences of mismatch on male and female earnings. Overall, despite differences in the levels of skill-task mismatch between men and women, consequences are similar for the two sexes: in most countries there is a negative effect of earnings on being under-skilled in either dimension, both for men and women. Relative to being well-matched, men and women experience a wage penalty of 5-9%. The effect is present both between and within occupations and controlling for both dimensions of mismatch weakens but does not cancel out their respective impact on wages. A secondary finding is that women benefit significantly more than men from being over-skilled in numeracy, but the size of the effect is small and disappears within occupations for all but Eastern European countries. In terms of explaining the gender wage-gap, I find that mismatch in literacy or numeracy does not help explain part of the gender earnings gap in the traditional Mincer model.

The rest of this paper is organised as follows: section 2.2 outlines the literature review; section 2.3 explains the data; section 2.4 presents the mismatch measure; section 2.5 shows some stylised facts about mismatch for the two genders; section 2.6 presents the econometric model to study the effect of mismatch on wages; and section 3.5 presents the results.

2.2 Literature Review

As mentioned in Chapter 1, a number of papers have already studied the negative outcomes of multi-dimensional mismatch for the male sample. Fredriksson et al. (2018) find that being mismatched early in one's career is relatively common but does not have wage consequences, whereas being mismatched later in one's career is much rarer but is accompanied by a negative wage impact. Guvenen et al. (2015) find that being mismatched in literacy correlates with slower wage growth over the course of the match. Estimating a model of on-the-job search, Lise and Postel-Vinay (2015) find that individuals could gain between 8 and 22% higher wages over their working life if they would enter a better match early on.

The common drawback of the previous studies is that they have only been studied for the male workforce, due to a lack of available test data on the skills of women. The skills tests used by Guvenen et al. (2015), Lise and Postel-Vinay (2015) and Fredriksson et al. (2018) are the result of compulsory military IQ tests. Since women in the US and Sweden - the countries from where data is used - do not have to enter military service, these test are only available for the male population. There are currently no papers looking at the extent to which the female labour market outcomes are affected by mismatch of different skills to their respective job tasks. More generally speaking, the role of mismatch in explaining gender earnings-gaps has not been studied either from a general equilibrium approach, or in traditional survey-based studies, nor in experimental set-ups (see Azmat and Petrongolo (2014) for an overview of research directions and methodological approaches in explaining the gender gap in earnings and wages.). While we cannot directly replicate the existing results of multi-dimensional mismatch for the female population since PIAAC is not longitudinal, we fill a gap by providing a set of new stylised facts about female relative to male multi-dimensional mismatch in cross-section data in European countries, as well as consequences for female earnings and the male-female earnings gap.

Despite the lack of work on mismatch and gender, a number of studies do look at male and female skills and their impact on labour market outcomes, such as earnings, using the PIAAC dataset. de la Rica and Rebollo (2017) study gender-gaps in numeracy and literacy, also using PIAAC, and find that men have slightly higher scores in numeracy (20% of a standard deviation higher). In literacy, they find no significant differences between men and women. Furthermore, they show that about 12% of the observed gender wage gap can be explained by the differences in numeracy skills. A similar conclusion is reached by Hanushek et al. (2015), who also use the PIAAC data.

2.3 Data

I use the 1st round of the Programme for the International Assessment of Adult Competencies (PIAAC), which was conducted between 2008 and 2013 by the Organisation for Economic Cooperation and Development (OECD). Unfortunately, the majority of the countries surveyed for PIAAC are missing one or more of the variables required for the current analysis and had to be excluded from the sample.[3] The nine countries used in this study are: Belgium, The Czech Republic, Denmark, France, Italy, The Netherlands, Poland, Slovakia and Spain. I choose to group countries in order to facilitate comparisons and keep enough observations per cluster. The grouping is as follows: Northern Europe includes Flanders(Belgium), Denmark and the

[3]For example, Germany, Estonia, Finland, Ireland and Sweden do not have occupational categories. The US does not provide earnings information and the UK has missing earnings values for close to 40% of the sample.

Netherlands; Southern Europe includes France, Italy and Spain and Centra Europe includes the Czech Republic, Poland and Slovakia. The dataset contains information on demographic characteristics, earnings, employment status and occupational categories. Most importantly, we have access to contemporaneous measures of skills and job-tasks for both males and females and these variables are comparable across different countries. PIAAC is a cross-section dataset.

Table 2.1: Summary Statistics

	BEL	**CZE**	**DNK**	**FRA**	**ITA**	**NLD**	**POL**	**SVK**	**ESP**
Sample Size	2,721	2,648	4,466	3,681	1,823	3,203	3,930	2,485	2,475
Female	0.48	0.50	0.49	0.48	0.44	0.48	0.43	0.47	0.47
Log of montly earnings (PPP adjusted)	8.01	7.12	8.06	7.67	7.69	7.76	7.01	7.06	7.56
% Full-Time	0.74	0.91	0.82	0.83	0.83	0.59	0.89	0.94	0.82
Age 16-25	0.12	0.16	0.12	0.10	0.07	0.17	0.45	0.11	0.10
Age 26-35	0.24	0.27	0.16	0.22	0.21	0.18	0.23	0.25	0.25
Age 36-45	0.27	0.24	0.23	0.27	0.35	0.24	0.13	0.26	0.23
Age 46-55	0.28	0.19	0.24	0.28	0.26	0.23	0.12	0.26	0.24
Age 56-65	0.10	0.14	0.25	0.14	0.12	0.16	0.07	0.12	0.11
Primary School	0.03	0.00	0.01	0.05	0.04	0.06	0.01	0.00	0.16
Lower Secondary	0.09	0.08	0.17	0.14	0.25	0.20	0.07	0.09	0.24
Upper Secondary	0.41	0.64	0.35	0.44	0.48	0.40	0.55	0.67	0.20
Professional Degree	0.29	0.07	0.24	0.14	0.02	0.04	0.06	0.01	0.12
Bachelor	0.02	0.04	0.08	0.12	0.19	0.21	0.10	0.04	0.13
Master/PhD	0.16	0.18	0.15	0.12	0.03	0.10	0.22	0.20	0.16

[1] 'Full-time' refers to individuals working more than 35 hours a week.
[2] We use monthly earnings, since hourly wages had a large number of missing values.
[3] The sample includes employed individuals only (no self-employed).

I focus on individuals aged 16-65 years, who are employed full-time (excluding the self-employed). In terms of sample sizes, there is some variation between different countries, the smallest sample being from Italy and the largest from Denmark. Northern European countries (Belgium, Denmark and the Netherlands) have the lowest proportion of individuals working full-time, with the Netherlands having only 59% of the population in full-time employment. We control for the above characteristics.

2.4 Measuring Mismatch using Skills and Tasks

In this section I introduce the skills and tasks measures available in the PIAAC dataset and upon which I construct a measure of mismatch to compare male versus female mismatch. The major advantage of this particular dataset is that for both numeracy and literacy we have information not only on the individual's skill level in that particular dimension but also on the frequency with which they do tasks that use those particular skills. It is not yet a standard practice in the literature to study mismatch by comparing one's skill level to one's use of the tasks that use that skill the most, relative to others in similar occupations. In other datasets that have been used to study mismatch, we either only have the skills information (e.g. Swedish administrative data in Fredriksson et al. (2018)) or we can have both but with the tasks not being at the individual level (e.g. the American NLSY in Guvenen et al. (2015)). PIAAC combines detailed information on both skills and tasks, at the individual level, allowing for a definition of mismatch that incorporates the assumption that the more able workers in a given dimension (e.g. literacy) should be expected to do more of the tasks using the skill in which they have a comparative advantage, an assumption that cannot be exploited when either the skills or the tasks at the individual level are missing. PIAAC also contains information on manual, social and problem solving tasks, however I do not include these in the current analysis due to i) the lack of corresponding skill information on manual and social skills and ii) the large number of missing observations for the tests on problem solving skills.

2.4.1 Skills measures in PIAAC

Respondents in the PIAAC survey are tested in two main skills: literacy and numeracy. The test materials are made up of a battery of 114 standardised test questions (58 literacy and 56 numeracy items), examples of which can be seen in Appendix B. The respondents do not answer all 114 questions - the test is designed to be attributed in stages. In the first stage, respondents answer three easy literacy and numeracy questions, to determine whether they should continue with the assessment. If they pass, respondents are then randomly assigned to take a literacy, numeracy or problem solving test consisting of 9 questions in the first round, before being randomly re-assigned to take a second round of questions in either of the topics they haven't taken, now consisting of 11 questions. The literacy and numeracy assessments are offered in the country's local language and have an adaptive design, i.e. respondents are directed to different blocks of items based on their estimated ability (OECD (2013)).[4] The test scores range from 0 to 500 and are calculated following the principles of Item Response Theory (ITM), where the answers of all respondents in all countries are used to estimate a model that produces a skill proficiency measure for each participant. This method of deriving skills measures affects the way in which the data has to be subsequently used: all statistics and estimations for the skills scores have to be calculated using jackknife standard errors (OECD (2013)).[5]

Table 2.2 shows the average level of skills by region and gender. Northern Europe tends to have higher scores in both numeracy and literacy relative to the Southern and Eastern Europe. Men in Northern Europe tend to have much higher numeracy

[4]Around 23% of the sample averaged across all participating countries (i.e. taking into account countries not included in this study) took a paper-based assessment, instead of a computer-based one. These were people who either failed to pass a basic ICT skills test at the beginning of the assessment or who chose to take the test with pen and paper, despite being computer literate. The structure of the test is different for this group: in the first stage they complete 4 literacy and 4 numeracy questions. In the second stage, they are randomly assigned to complete 20 questions in either literacy or numeracy and subsequently everyone completes a reading component.

[5]In addition to literacy and numeracy, skills measures were obtained for problem solving too. I will not be using the problem solving tests since up to 30% of the respondents per country have not taken the problem solving test, which leads to worries of sample selection. All respondents have taken both the numeracy and literacy tests.

Table 2.2: Average skill scores by region and gender

	Northern Europe	**Southern Europe**	**Eastern Europe**
Literacy	287	262	274
Numeracy	287	259	271
Female			
Literacy	286	261	277
Numeracy	281	262	270
Male			
Literacy	287	263	272
Numeracy	293	255	272

The maximum score is 500. Scores are weighted using country weights provided by PIAAC. Norhtern Europe includes Flanders, Denmark and The Netherlands; Southern Europe includes France, Italy and Spain; and Eastern Europe includes Czechia, Poland and Slovakia.

scores than women, but not in the other regions. The higher male scores in Northern Europe are present in the entire distribution and are not driven only by outliers, as can be seen in the 2nd row of Table 2.3. In Table 2.3, we also see that women tend to outperform men in the lower ranks of the skill distribution, while the opposite is true in the higher ranks. The latter characteristic of the data has been previously observed in IQ-type tests - thus it is not a 'quirk' of the PIAAC tests.

2.4.2 Task measures in PIAAC

The survey contains information on different types of tasks encompassing cognitive skills, technology, interaction with others, learning, organisation and physical work. Since we only have test information on the cognitive skills of individuals, in order to measure mismatch we focus on cognitive tasks only. The cognitive job tasks are categorised in two dimensions: numeracy and literacy (reading and writing) and can be seen in table 2.4 (OECD (2013)). Individuals self-report whether they undertake the tasks in their current job. Each of the tasks varies in intensity within a score of

Table 2.3: Skills quintiles by gender

	p1	p25	p50	p75	p99
Northern Europe					
Male					
Literacy	153	260	292	319	380
Numeracy	148	265	297	325	391
Female					
Literacy	171	260	290	315	375
Numeracy	159	253	284	311	374
Southern Europe					
Male					
Literacy	134	230	264	295	359
Numeracy	120	228	265	299	369
Female					
Literacy	140	234	266	294	354
Numeracy	121	224	258	289	355
Eastern Europe					
Male					
Literacy	155	244	275	302	367
Numeracy	142	242	274	305	375
Female					
Literacy	168	249	277	305	374
Numeracy	154	240	272	301	371

The maximum score is 500. Scores are weighted using country weights provided by PIAAC. Northern Europe includes Flanders, Denmark and The Netherlands; Southern Europe includes France, Italy and Spain; and Eastern Europe includes Czechia, Poland and Slovakia.

Table 2.4: Literacy and Numeracy Tasks

Literacy tasks	**Numeracy tasks**
read directions or instructions	calculating costs or budgets
read letters, memos or e-mails	use or calculate fractions or percentages
read newspapers or magazines	use a calculator
read professional journals or publications	prepare graphs, charts or tables
read books	use simple algebra or formulas
read manuals or reference materials	use advanced math or statistics
read financial statements	
read diagrams, maps or schematics	
write letters	
write articles	
write reports	
fill in forms	

0-5, where 0 means "I never do the task" and 5 means "I do the task everyday".

2.4.3 Measuring Skill-Task Mismatch

Once the four distributions have been computed (i.e. one skill score distribution and one job-task intensity distribution for each of numeracy and literacy), the skill-task measure of mismatch consists of comparing one's position in the skill distribution to their position in the task distribution. To give an example, if someone is in the top 10% of the numeracy skill distribution but in the top 40% of the numeracy task distribution, this person would be mismatched and this could be interpreted in one of two ways: they would be 'over-skilled' in the sense that given their position in the task distribution they have too much skill compared to their peers; or they would be 'under-tasked' in the sense that given their position in the skill distribution, they are doing too little of the tasks that best suit their high level of numeracy skill.

The simplest way to obtain a measure of mismatch from the comparison of these two distributions is by subtracting each individual's position on the task distribution from their position on the skill distribution:

$$\text{Mismatch}_i = \text{Skill Position}_i - \text{Task Position}_i, \tag{2.1}$$

where the units of Mismatch are percentage point differences between the skill distribution and the task distribution. If $Mismatch_i$ is positive then the individual is over-skilled (or under-tasked) and if it is negative then the individual is under-skilled (over-tasked). Since the measure is continuous, we do not observe any perfect zeros in the data.

It is worth noting that this measure takes on both positive and negative values, meaning that in a Mincer regression a unit increase will be interpreted as a decrease in mismatch if it is on the negative side of the measure, but as an increase in mismatch if it is on the positive side. Given previous studies on the differential effects of being over-skilled versus being under-skilled on wages, it is not expected that the absolute value of the partial effect will be the same along the positive and negative side of the distribution.

2.5 Skill-Task Mismatch by gender: stylised facts

To compare the level of mismatch between men and women I look at the distribution of Skill-Task mismatch for men and women separately, and by skill dimension. I first compare at the country level in subsections 2.5.1 and 2.5.2 and also show overall results by Northern, Southern and Eastern Europe.

2.5.1 Mismatch in Literacy is similar for men and women

For each of the nine countries and the three regions I display the distributions of skill-task mismatch for the two genders. The left panel of figures 2.1-2.9 and figures 2.10-2.12 shows the difference in literacy skill-task mismatch between men and women.

The dotted line is men and the solid line is women. There is a tendency for women to be more over-skilled than men (the female density is to the right of the male density) in Eastern Europe (Poland, Czech Republic and Slovakia), while the opposite is true in Southern Europe (France, Italy and Spain). In Northern Europe, Belgium and the Netherlands have slightly more over-skilled women, while in Denmark there are more over-skilled men. Nevertheless, a set of Kolmogorov-Smirnov (KS) tests for the similarity of the mismatch distributions of the genders in table 2.5 on the LHS column, shows that in most countries there isn't a significant difference between men and women in literacy mismatch.[6] The only conclusive evidence is for France, where the null of identical distributions is rejected.

2.5.2 Mismatch in Numeracy is different for men and women and by region

The right panel of figures 2.1-2.9 and figures 2.10-2.12 shows the difference in Numeracy skill-task mismatch. As before, the dotted line is for men and the solid line is women. Unlike in literacy, numeracy shows a clear divide between Northern Europe and the South and East: in Northern Europe, there are more over-skilled women than men, and more under-skilled men than women, i.e. the female mismatch distribution is to the right of the male one, along all points. The opposite is true in Southern and Eastern Europe: the male distribution is to the right of the female, suggesting that there is more male mismatch (with the exception of the Czech Republic, which has a pattern similar to Northern Europe). The KS tests of table 2.5 RHS column show that for most countries the null of identical numeracy mismatch distributions between men and women is rejected, showing that the gender differences present in the graphs are statistically significant. The results for Northern Europe can be considered in conjunction with previous research by de la Rica and Rebollo (2017)

[6]Since for each individual we have 10 plausible values for the literacy skill score and 10 for the numeracy, I run the KS test for each plausible value, for each skill and for each country separately. In table 2.5 I summarise the outcomes for ease of interpretation. In all cases the KS test provides very similar results for each plausible value. Detailed results in Appendix A.

and Hanushek et al. (2015), who both find that womens' absolute average numeracy skill-level is lower than that of the men. Here we find that, despite lower absolute levels in numeracy, women in Northern Europe are more likely to be over-skilled in that dimension relative to the men, while also less likely to be under-skilled, relative to men.

Table 2.5: Kolmogorov-Smirnov test of similarity of skill-task mismatch distributions by gender

	KS tests	
	Literacy	Numeracy
BEL	Null not rejected	Null not rejected
DNK	Null not rejected	Null rejected at 5%
NLD	Null not rejected	Null rejected at 5%
ESP	Null not rejected	Null rejected at 5%
ITA	Null not rejected	Null not rejected
FRA	Null rejected at 1%	Null not rejected
POL	Null not rejected	Null rejected at 1%
SVK	Null not rejected	Null rejected at 5%
CZE	Null not rejected	Null rejected at 10%

H_0 : male distribution = female distribution
H_a : male distribution $\neq$ female distribution
Since each individual has a set of 10 plausible values for their literacy and numeracy scores respectively, we have run KS tests for each of the PV separately and have aggregated the results in this table, to ease reading. The detailed results can be found in Appendix A.

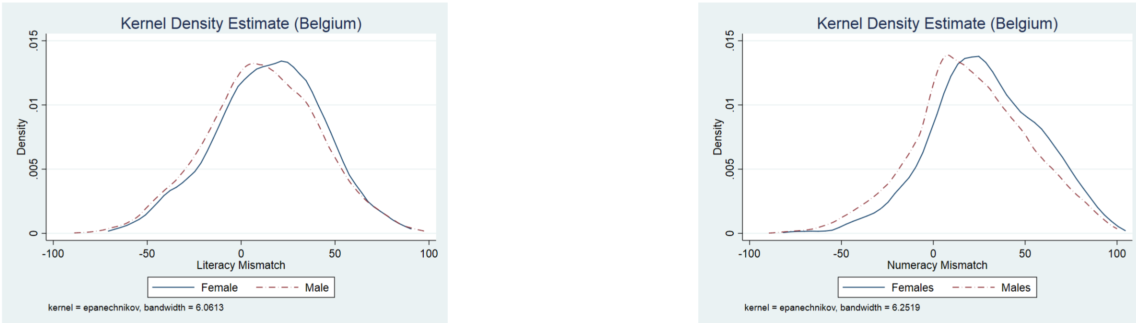


Figure 2.1: Belgium

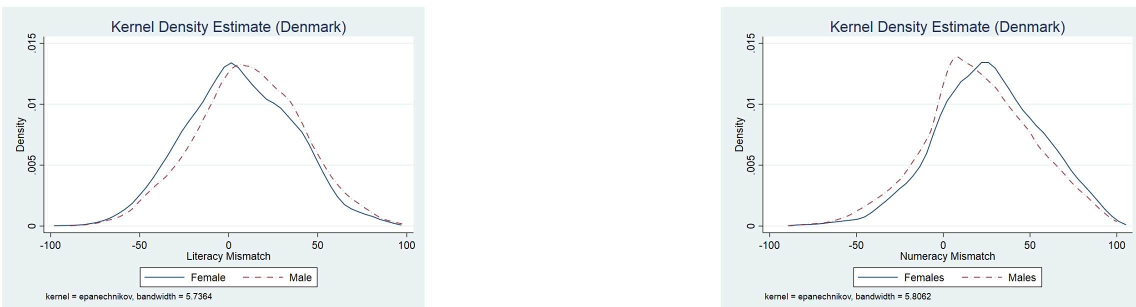
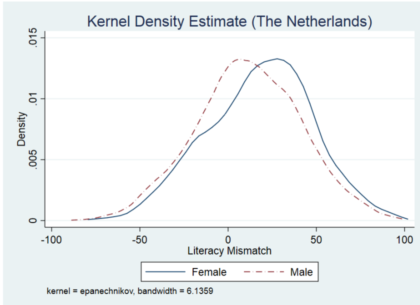


Figure 2.2: Denmark



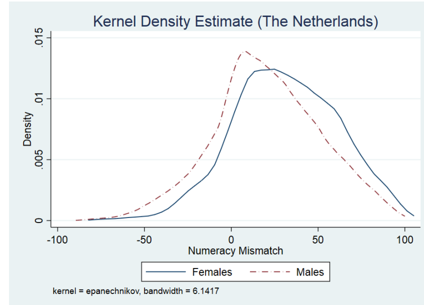
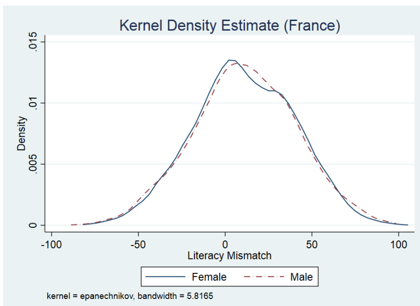


Figure 2.3: The Netherlands



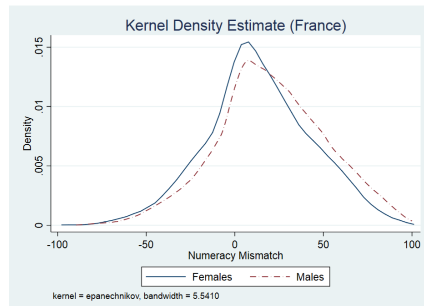
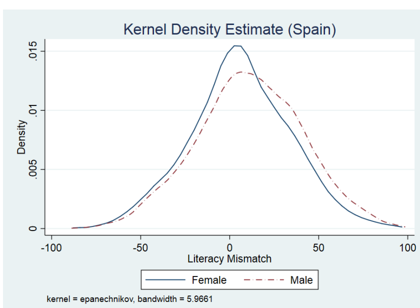


Figure 2.4: France



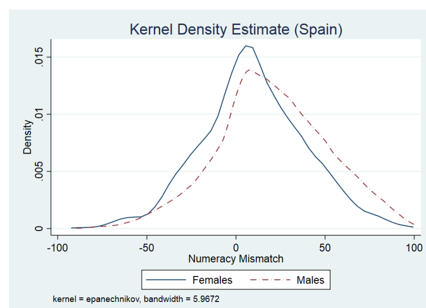


Figure 2.5: Spain

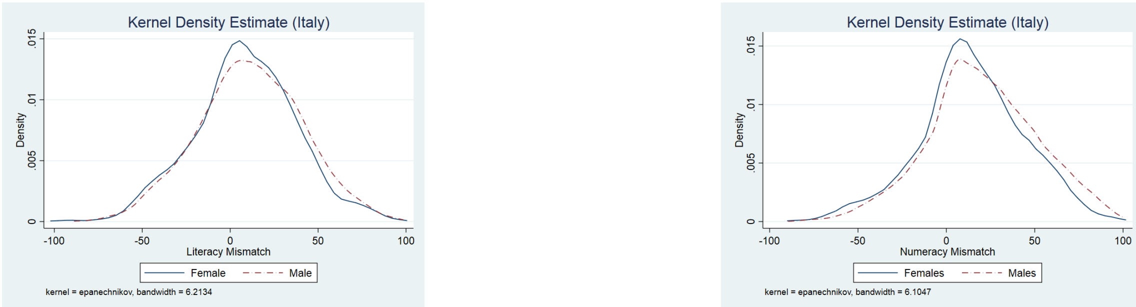


Figure 2.6: Italy

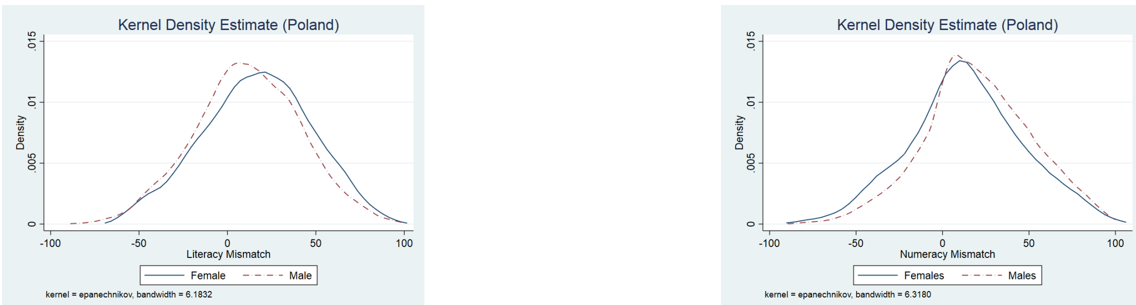


Figure 2.7: Poland

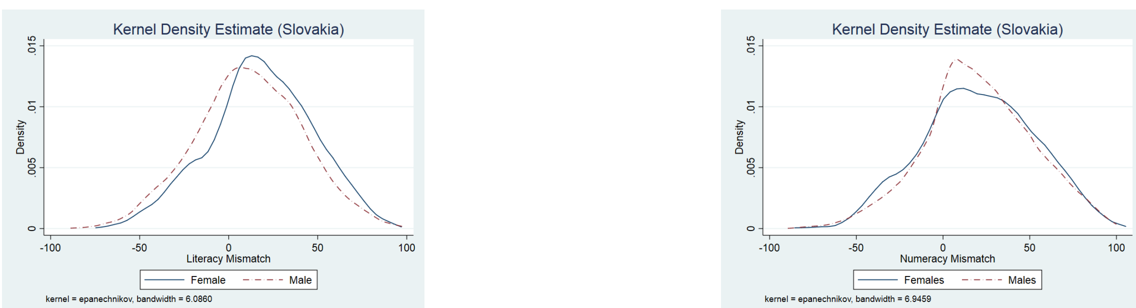


Figure 2.8: Slovakia

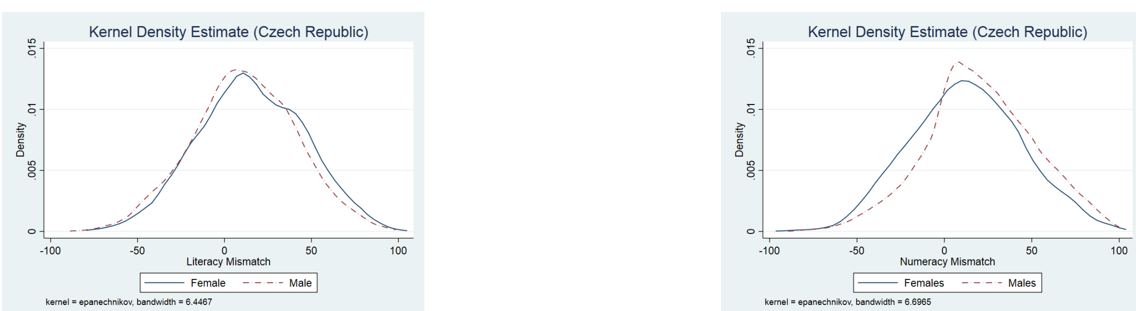


Figure 2.9: Czech Republic

Figure 2.10: Northern Europe

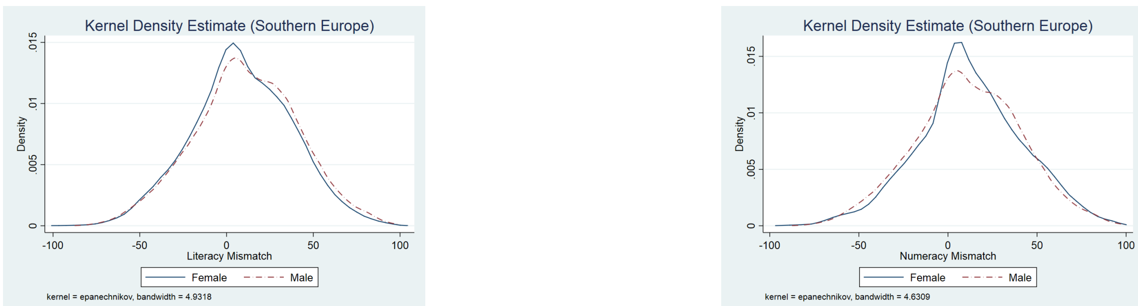


Figure 2.11: Southern Europe

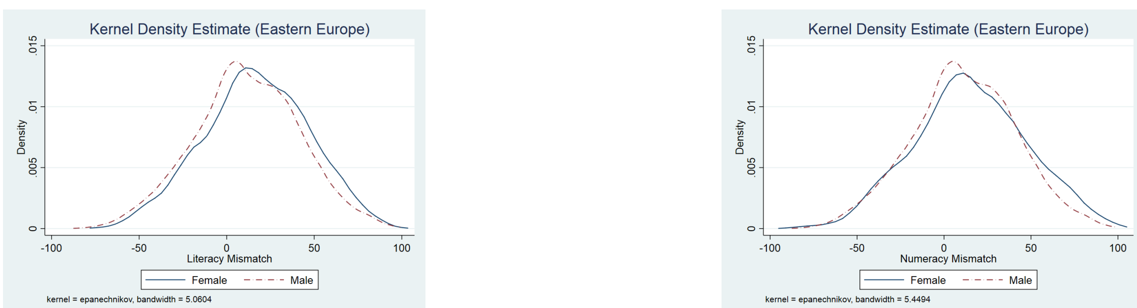


Figure 2.12: Eastern Europe

2.6 Wages and Skill-Task Mismatch by gender

2.6.1 Econometric Model

I use a reduced form model to study the correlation between skill-task mismatch and wages for the men and women. The equation is:

$$
\begin{aligned}
lnw_i &= \beta_0 + \beta_1 female_i + \sum_{j=1}^{2}\Big[\beta_{1j} Underskilled_i + \beta_{2j} Overskilled_i + \beta_{3j} Underskilled_i * female_i \\
&+ \beta_{4j} Overskilled_i * female_i + \gamma_{1j} Skill_i + \gamma_{2j} Skill_i^2 + \gamma_{3j} Task_i\Big] + X_i\beta + \alpha_{ki} OCC_{ki} + v_i
\end{aligned}
$$

where j=1,2 are the two dimensions of skill, namely numeracy and literacy; i stands for individuals and k for occupations. The dependent variable is the log of monthly ppp-adjusted earnings. The independent variables of interest are 'Underskilled', which is equal to 1 if the individual has a mismatch score less than -0.20 and 0 otherwise; 'Overskilled' is equal to 1 if the individual has a mismatch score higher that 0.20, and 0 otherwise. Choosing the threshold of 0.2 is a means to focus on those with the highest levels of mismatch, without losing too many observations. Since the distribution of mismatch is bell-shaped, the majority of the sample experiences some amount of small to medium-level mismatch. Thus the observations at the tail ends of the distribution represent those with the highest level of mismatch only. The dummies 'over/underskilled' are formulated separately for numeracy and literacy. The reference category, which is not included in the regression, is equal to 1 if the individual is well-matched, i.e. their mismatch score is $-0.20 < x < 0.20$. In the estimations, I run the model both with and without controlling for the second dimension of mismatch to overcome potential problems of complementarity between the two types of mismatch - that is, if being mismatched in one dimension is correlated with also being mismatched in the other dimension. To disentangle differential effects between men and women, I add two multiplicative dummies named 'overskilled*female' and 'underskilled*female'. These will allow us to study if the effect of mismatch in each of the two dimensions is different by gender. I also add the 'female' dummy.

Additional control variables of interest are the skills and tasks. I add a 2^{nd} order polynomial for each of the skill dimensions. The Task variable controls for how intensively the individual performs numeracy and literacy tasks on the job. The task variables have been normalised to range between 0 and 1, where 1 is the highest intensity level and 0 is the lowest, i.e. the individual never performs any tasks in that dimension. Since we are interested in testing for the correlation between mismatch and wages, which might be influenced by the individual's absolute skill rank or absolute task intensity rank, we control for both skill score and task ranks to avoid bias. A simple example of bias is the situation where the individual's absolute high or low skill score is a much stronger predictor of wages, rather than their level of mismatch relative to the rest of the population. Adding a 2^{nd} order polynomial in each of the skills allows us to control for a potential non-linear relationship between the skill-level and wages, in particular for individuals at the extremes of the distribution. Keeping skill score and task intensity constant in the regression allows us to infer that the correlation between mismatch and wages is not driven by high or low skill scores, but by mismatch.

In terms of demographic controls, I add age and age squared, since Fredriksson et al. (2018) show that younger workers are more likely to suffer from mismatch. Younger workers also have less experience, which translates to lower wages on average. By controlling for the individual's age, we can exclude the possibility that the correlation between mismatch and wages is only due to younger workers being more mismatched and having less labour market experience. I also add a set of educational dummies going from primary school to a master's degree, since these are well-known predictors of wages. As can be seen in the summary statistics table 2.1, an important proportion of the Northern European sample does not work full-time, so I also control for hours worked. Finally, to obtain a correlation between mismatch and wages among individuals doing identical jobs, I add a set of occupational controls at the 4-digit level of dis-aggregation. This allows me to compare whether the correlation between skill-task mismatch and wages is a between-occupations phenomenon driven by the different characteristics of occupations or whether it persists within occupations.

To allow for a level of comparison among countries, without losing too much statistical power, I group the nine countries of the sample into Eastern, Northern and Southern Europe. Eastern Europe has the Czech Republic, Poland and Slovakia; Northern Europe includes Belgium, The Netherlands and Denmark; and Southern Europe includes Italy, France and Spain.

As is the case with most mismatch studies, this analysis can be vulnerable to criticisms of selection bias and measurement error. Selection bias is a potential issue since we have not randomly 'treated' individuals with higher or lower levels of mismatch to understand how it might impact their wages. Nevertheless, we have controlled for an extensive number of observable individual and job-related characteristics to allow for the highest level of comparability possible. Furthermore, since skill-task mismatch is a multi-layered measure that we can observe only once the match between the worker and the job has been realised and which the worker cannot know in advance, it is less likely to be influenced by the type of selection that is present in education decisions, whose outcomes on wages depend directly on the individual's choices.

Another possible worry is measurement error in our variables of interest, i.e. the skill and task distributions which are used to construct the mismatch variable. The skills scores have been obtained by running a set of cognitive tests, similar to the ASVAB Military Tests that are run in the US. As for the tasks, the main drawback of PIAAC is that the tasks that are explicitly measured are majoritarily cognitive in their nature. Manual tasks are largely ignored by the survey, which means that all results will be driven by mismatch in the cognitive dimension and not the manual. Thus, the results are likely to be under-estimating the true effect of mismatch, since we are only looking at the cognitive part of the economy.

2.7 Results

Tables 2.6-2.8 show the results for the effect of numeracy and literacy mismatch on male and female earnings. Table 2.9 shows the extent to which skill-task mismatch explains the gender earnings-gap. In each table, the estimations are divided by region: Northern Europe (Belgium, Denmark and The Netherlands), Southern Europe (France, Italy and Spain) and Eastern Europe (Czech Republic, Poland and Slovakia). Results are presented with and without occupational fixed effects.

2.7.1 Literacy mismatch

Table 2.6 shows the effect of being over- or under-skilled in literacy on the log of ppp-adjusted monthly earnings. We first see that, for both sexes, being under-skilled in literacy is significantly negatively correlated with wages, before we control for occupations. Furthermore, in columns (2)-(3), we see that women appear to be less affected by mismatch financially, relative to the men - if anything, being under-skilled appears to have small positive effect on earnings.

In columns (4)-(6) of table 2.6 we add occupational fixed effects in the regressions to study whether the apparently similar effects of mismatch for the two sexes could be masked by occupational segregation. A large literature has shown that women are found in different occupations to men, while also getting paid less on average (eg. Goldin (2014); Blau et al. (2013); Macpherson and Hirsch (1995)). By adding a set of 4-digit occupational dummies in both the female and male estimations, we can study whether mismatch coefficients are correlated with occupations in the same way for the two genders and whether women's choices affect their level of mismatch relative to men's choices. For most regions, with the exception of Northern Europe, we see that the coefficients are weakened, suggesting that skill-task mismatch is closely related to occupational choice and segregation. In Southern Europe the negative coefficient on being under-skilled in column (2) disappears once we control for occupations, in column (5). It is now clearer that once occupational segregation is taken into account being mismatched in literacy has very symmetric outcomes for male and female wages.

As a robustness check, we choose to also control for the level of numeracy mismatch, since the two types of mismatch could be correlated. If a worker is mismatched in one dimension, he/she could also be mismatched in the other dimension. The results are shown in table 2.8 and we see that while the direction and significance of the outcomes for literacy mismatch does not change, the size of the coefficient decreases slightly. We still see a negative effect of being under-skilled in literacy for both men and women in Northern Europe, although the statistically weaker effect for Eastern Europe now disappears.

2.7.2 Numeracy mismatch

Table 2.7 shows the effect of mismatch in numeracy on monthly earnings for the two genders. Unlike with literacy, for most countries there is a strong significant negative effect of mismatch on earnings, both before and after controlling for occupational fixed effects. Comparing the coefficients on *under_num* in columns 1-3 an 4-6 shows almost no differences, both in size and statistical significance. Furthermore, unlike in literacy, we see that the negative effect of mismatch affects primarily the male population, with the exception of Northern Europe where it affects both sexes equally.

We then move to table 2.8 to study the effect of numeracy mismatch, when also controlling for literacy mismatch. The negative effect of being under-skilled in numeracy remains for both men and women, but it is now present only within occupations. We do not see any differences in how mismatch affects earnings for men and women. Unlike in literacy, we find that the effects are exactly alike for men and women. Relative to men, women appear to obtain a small financial gain from mismatch, although it is primarily due to the lack of occupation controls. Once controlling for occupations, the female advantage to being mismatched in numeracy is only present for Eastern Europe. Overall, however, men and women are similarly affected by mismatch in numeracy in their wages.

2.7.3 Mismatch and the earnings gap

In table 2.9 we study the extent to which adding mismatch in an earnings model explains any of the gender earnings gap. Controlling for demographics, education and hours worked, the coefficient on female is an average of -0.16, i.e. women's monthly earnings are 16% lower than men's.[7] Controlling for mismatch variables in columns 4-6, we obtain slightly higher average coefficient on female, of -0.18. Testing for the significance in the different coefficients, we do not find any differences, except for Northern Europe where the difference is quite small at 1 percentage point. This outcome is not surprising, since mismatch was a significant predictor of earnings only in Northern and not in the rest of the European countries of this sample.

2.8 Conclusion

Ever since the introduction of the study of multi-dimensional mismatch, data samples have been exclusively male. Comparing multi-dimensional mismatch for both the male and female sample allows us to obtain an estimate for whether previous results are likely to hold for both sexes. The PIAAC dataset is a good starting point since it provides contamporaneous information on the skills and tasks of both men and women, unlike previous datasets. In this paper, we provide the first set of stylised facts about multi-dimensional mismatch for women and how it compares to male multi-dimensional mismatch.

Using two dimensions of mismatch, literacy and numeracy, we find that literacy mismatch is similar for the two sexes. For numeracy however, we find that in Northern Europe there is a pattern where we see more women with skills exceeding those required by the job, while at the men tend to lack required skills. To a lesser extent, the exact opposite distribution of mismatch for numeracy is observed in Southern

[7] We have taken the average coefficient from the first three columns of the table, where mismatch variables are excluded.

and Eastern Europe. We then test the extent to which mismatch is correlated with wages for the men and women, controlling for observable factors and 4-digit occupational categories. Overall, we do not find a strong correlation between mismatch and earnings for either men or women, except in Northern Europe. We find that there is a persistent negative effect on earnings for being under-skilled in each literacy or in numeracy and for both genders, regardless of occupational choice. Finally, we do not find strong evidence to suggest that mismatch might be a contributing factor to the gender earnings gap.

These results highlight that while observed mismatch is not the same among men and women in different skill dimensions, its consequences appear symmetric. Nevertheless, the question of how mismatch affects men and women over the life cycle remains open, and would be important to study when we have longitudinal data on skills and tasks for men and women.

2.9 Tables

Table 2.6: The wage effects of **literacy** skill-task mismatch for men and women

	(1) North	(2) South	(3) East	(4) North	(5) South	(6) East
under_lit	-0.08***	-0.06**	-0.05**	-0.07***	-0.03	-0.05*
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
female*under-skilled	0.02	0.07**	0.08**	0.01	0.03	0.06*
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
over_lit	0.02	-0.01	0.00	0.02	0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
female*over-skilled	-0.02	0.03	-0.03	-0.02	0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Lit_task	0.66***	0.77***	0.71***	0.48***	0.52***	0.54***
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)
Num_task	0.08***	0.01	-0.01	0.02	-0.04	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Lit_skill	0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Num_skill	0.00	0.00	-0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female (d)	-0.08***	-0.18***	-0.25***	-0.04***	-0.09***	-0.18***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Demographics	✓	✓	✓	✓	✓	✓
Education	✓	✓	✓	✓	✓	✓
4-digit OCC				✓	✓	✓
Country	✓	✓	✓	✓	✓	✓
N	10386	7963	9059	10386	7963	9059
R^2	0.714	0.547	0.450	0.742	0.623	0.525

[1] The dependent variable is the log ppp-corrected monthly wage. Controls include age, age squared, a set of 2nd order polynomials for the skills scores, five education dummies, hours worked. Country dummies are different for each region: in Northern Europe we have Belgium, Denmark and the Netherland; in Southern Europe we add France, Italy and Spain and in Eastern Europe we add the Czech Republic, Poland and Slovakia. Columns 1-3 perform the estimations without occupational fixed effects and columns 4-6 control for 253 4-digit occupations. (d) is for discrete change of dummy variable from 0 to 1.
SE in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: The wage effects of **numeracy** skill-task mismatch for men and women

	(1) North	(2) South	(3) East	(4) North	(5) South	(6) East
under_num	-0.07***	-0.06**	-0.06**	-0.07***	-0.05**	-0.07**
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
female*under-skilled	0.00	0.10***	0.07**	0.01	0.06*	0.07*
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
over_num	0.04**	-0.02	-0.01	0.04**	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
female*over-skilled	-0.03	0.04**	0.04	-0.03	0.02	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Lit_task	0.55***	0.74***	0.71***	0.39***	0.49***	0.53***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Num_task	0.18***	0.02	0.02	0.12***	-0.02	0.03
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
Lit_skill	0.00	-0.00	0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Num_skill	-0.00	0.00	-0.00*	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.07***	-0.19***	-0.28***	-0.03**	-0.10***	-0.21***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Demographics	✓	✓	✓	✓	✓	✓
Education	✓	✓	✓	✓	✓	✓
4-digit OCC				✓	✓	✓
Country	✓	✓	✓	✓	✓	✓
N	10386	7963	9059	10386	7963	9059
R^2	0.714	0.547	0.449	0.742	0.623	0.526

[1] The dependent variable is the log ppp-corrected monthly wage. Controls include age, age square, 2nd order polynomials for the skills cores, five education dummies, hours worked. Country dummies are different for each region: in Northern Europe we have Belgium, Denmark and the Netherland; in Southern Europe we add France, Italy and Spain and in Eastern Europe we add the Czech Republic, Poland and Slovakia. Columns 1-3 perform the estimations without occupational fixed effects and columns 4-6 control for 253 4-digit occupations. (d) is a dummy variable.
SE in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: The wage effects of skill-task mismatch for men and women: **literacy & numeracy**

	(1) North	(2) South	(3) East	(4) North	(5) South	(6) East
under_lit	-0.07***	-0.05**	-0.05*	-0.05***	-0.02	-0.04
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
female*under-skilled_lit	0.02	0.06*	0.08**	-0.00	0.02	0.06*
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)
over_lit	0.01	0.00	0.01	0.01	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
female*over-skilled_lit	-0.01	0.01	-0.06**	-0.01	0.01	-0.03
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
under_num	-0.06**	-0.05	-0.04	-0.06**	-0.05*	-0.05*
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
female*under-skilled_num	-0.00	0.08**	0.04	0.01	0.05	0.04
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
over_num	0.03**	-0.02	-0.02	0.03*	-0.01	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
female*over-skilled_num	-0.02	0.05**	0.07***	-0.03	0.02	0.06**
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Lit_task	0.65***	0.78***	0.70***	0.47***	0.52***	0.53***
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)
Num_task	0.16***	0.01	0.03	0.10**	-0.02	0.03
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
Lit_skill	0.00	-0.00	0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Num_skill	0.00	0.00	-0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female	-0.07***	-0.20***	-0.27***	-0.03*	-0.10***	-0.21***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Demographics	✓	✓	✓	✓	✓	✓
Education	✓	✓	✓	✓	✓	✓
4-digit OCC	-	-	-	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓
N	10386	7963	9059	10386	7963	9059
R^2	0.714	0.547	0.450	0.742	0.623	0.526

The dependent variable is the log ppp-corrected monthly wage. Controls include age, age square, five education dummies, hours worked. Country dummies are different for each region: in Northern Europe we have Belgium, Denmark and the Netherland; in Southern Europe we add France, Italy and Spain and in Eastern Europe we add the Czech Republic, Poland and Slovakia. Columns 1-3 do not contain occupations fixed effects and columns 4-6 contain 253 4-digit occcupation dummies. (d) is a dummy variable.
SE in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: Skill-Task Mismatch and gender earnings gap

	North	South	East	North	South	East
under_num	-	-	-	-0.07**	-0.02	-0.04
				(0.03)	(0.02)	(0.03)
female*under-skilled_num	-	-	-	-0.00	-0.00*	-0.00
				(0.00)	(0.00)	(0.00)
over_num	-	-	-	-0.00	-0.03*	-0.01
				(0.01)	(0.02)	(0.02)
female*over-skilled_num	-	-		0.00	0.00***	0.00***
				(0.00)	(0.00)	(0.00)
under_lit	-	-	-	-0.07***	-0.02	-0.04
				(0.02)	(0.02)	(0.03)
female*under-skilled_lit	-	-	-	0.00	-0.00	-0.00**
				(0.00)	(0.00)	(0.00)
over_lit	-	-	-	0.04**	0.01	0.01
				(0.02)	(0.02)	(0.02)
female*over-skilled_lit	-	-	-	-0.00***	-0.00	-0.00***
				(0.00)	(0.00)	(0.00)
Lit_task	0.55***	0.73***	0.71***	0.63***	0.75***	0.66***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)
Num_task	0.08***	0.01	-0.01	0.13***	0.02	0.08
	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)
Lit_skill	0.00*	-0.00	0.00***	0.00	-0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Num_skill	0.00	0.00***	0.00***	0.00	0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female (d)	-0.08***	-0.16***	-0.26***	-0.07***	-0.19***	-0.27***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
N	10386	7963	9057	10386	7963	9057
R^2	0.713	0.547	0.448	0.715	0.547	0.450
Demographics	✓	✓	✓	✓	✓	✓
Education	✓	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓

[1] The dependent variable is the log ppp-corrected monthly wage. Controls include age, age square, five education dummies, hours worked. Country dummies are different for each region: in Northern Europe we have Belgium, Denmark and the Netherland; in Southern Europe we add France, Italy and Spain and in Eastern Europe we add the Czech Republic, Poland and Slovakia. Columns 1-3 perform the estimations without occupational fixed effects and columns 4-6 control for 253 4-digit occupations. (d) is a dummy variable.
SE in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Bibliography

AZMAT, G. AND B. PETRONGOLO (2014): "Gender and the labor market: What have we learned from field and lab experiments?" *Labour Economics*, 30, 32–40.

BLAU, F. D., P. BRUMMUND, AND A. Y.-H. LIU (2013): "Trends in occupational segregation by gender 1970–2009: Adjusting for the impact of changes in the occupational coding system." *Demography*, 50, 471–492.

COBB-CLARK, D. A. AND M. TAN (2011): "Noncognitive skills, occupational attainment, and relative wages," *Labour Economics*, 18, 1–13.

DE LA RICA, S. AND Y. REBOLLO (2017): "From Gender Gaps in Skills to Gender Gaps in Wages: Evidence from PIAAC," *Mimeo Universidad del Pais Vasco.*

FREDRIKSSON, P., L. HENSVIK, AND O. N. SKANS (2018): "Mismatch of talent: Evidence on match quality, entry wages, and job mobility," *American Economic Review*, 108, 3303–38.

GOLDIN, C. (2014): "A grand gender convergence: Its last chapter." *American Economic Review*, 104, 1091–1119.

GUVENEN, F., B. KURUSCU, S. TANAKA, AND D. WICZER (2015): "Multidimensional Skill Mismatch," *NBER Working Paper 21376.*

HANUSHEK, E. A., G. SCHWERDT, S. WIEDERHOLD, AND L. WOESSMANN (2015): "Returns to skills around the world: Evidence from PIAAC," *European Economic Review*, 73, 103–130.

Lise, J. and F. Postel-Vinay (2015): "Multidimensional skills, sorting, and human capital accumulation." *Manuscript, University of Minnesota*.

Macpherson, D. A. and B. T. Hirsch (1995): "Wages and gender composition: why do women's jobs pay less?" *Journal of Labor Economics*, 13, 426–471.

OECD (2013): *The survey of adult skills: Reader's companion*, OECD Publishing.

Chapter 3

The Task Content of Job Transitions over the Business Cycle: Evidence for the UK

Note: *This chapter is co-authored with Rachel J. Forshaw, a fellow PhD student at the University of Edinburgh. I have contributed towards the origin of the research question, the coding and data handling, the methodology, the estimation, the interpretation of results and the writing of the paper.*

3.1 Introduction

How do workers' job tasks change over the business cycle, if at all? A well-established literature has studied the extend to which individuals change their occupations and tasks when moving from one job to the next, as well as the consequences of such moves. Nevertheless, less is known about the extent to which the task content and difficulty are affected by current economic circumstances. In this paper, focusing on individuals who change employers, we study how the task content of their job is affected by the cycle.

Previously, the task content of job transitions has been studied by Poletaev and Robinson (2008), Gathmann and Schönberg (2010) and Robinson (2018), while the effect of the business cycle on career changes has been studied in Carrillo-Tudela et al. (2016). In this paper, we combine the two approaches and study the task content of jobs over the business cycle to bring additional insights into how recessions affect labour markets. Work by Deming and Kahn (2018) shows that skill requirements as found in job postings tend to be affected by economic conditions, with higher requirements observed during worse economic times. We complement this approach by looking at the content of the work, not in terms of the employer's requirements, but it terms of the employee's task portfolio and its change over the cycle. Until now, work on the cyclicality of tasks has been relatively sparse. Devereux (2000) offers an early study of the cyclicality of task assignment within the firm. Using US data he finds that firms tend to re-assign individuals to tasks of lower quality during recessions. His work focuses on task reassignment within the same employer, while we instead look at the cyclicality of task distance between different employers. Calibrating Canadian data on a search model with two-sided heterogeneity, Summerfield (2017) finds that an increase in the unemployment rate leads to an increase in the share of manual tasks found in job postings, leading to a higher risk of over-qualification during worse economic times. In our own work, we do not model job postings, but instead look at the change in the task content of realised matches of employment-to-employment transitions only, and among those we do not find a significant difference in the change of cognitive versus the manual task content.

Our first contribution is to study how the task composition of job transitions changes over the business cycle. We focus on the part of the working population that makes employment-to-employment (henceforth E2E) moves over the period 1997-2017 for the UK, either without interruptions, or with a short unemployment spell in-between (fewer than 3 months). We use the UK Labour Force Survey, which we map to task information at the 4-digit occupational level, using the US O*NET dataset. Previous research by Carrillo-Tudela et al. (2014) focuses on how recessions affect the probability of changing occupations - in this paper, we extend this line of enquiry to study situtations where an individual changes tasks, not just occupations. Moreover, the task content of transitions across occupations can be more similar than transitions within the same occupation. For example, in Table 3.1, moving from being an 'Air-conditioning and refrigerator engineers (5225)' to being an 'IT engineers (5245)' would not count as an occupational transition according to Carrillo-Tudela et al. (2014), even though the difference in tasks according to our analysis would be larger than moving to being a 'Audio-visual and broadcasting equipment operators (3417)', which is in a different 1-digit category.

Table 3.1: Occupational move and Task Distance

From	**To**	**Measure of Task Distance**
Air-conditioning & refrigeration engineers (**5**225)	IT engineers (**5**245)	0.10
Air-conditioning & refrigeration engineers (**5**225)	Audio-visual and broadcasting equipment operators (**3**417)	0.06

Using the above observation, we study whether individuals transition to more similar or dissimilar tasks during recessions using a measure of vector distance from Gathmann and Schönberg (2010). We characterise each occupation as a vector of tasks and we subsequently measure the angular separation between two occupations (i.e. vectors). The smaller the angle between the two vectors, the more similar is the task profile of the two occupations, and vice versa. We find that the business cycle has an economically significant effect on both the task distance between jobs as well as the task difficulty. In particular, a one percentage point increase in the unemployment rate leads to a decrease in the task distance of two jobs, conditional on an E2E transition. In other words, during times of higher unemployment individuals are more likely to move to jobs with tasks similar to what they did before. We then delve further into the type of transitions by looking at whether recessions accelerate the move away from or towards routine/non-routine tasks, as well as manual/cognitive tasks. We do not find a significant difference in terms of the routine/ non-routine dimension – i.e. the business cycle does not affect whether an individual moves to a more or less routine-intensive occupation.

Our second contribution is to study whether individuals going through E2E transitions tend to up- or down-skill during recessions. In addition to having a detailed outline of the task profile of each occupation, the US O*NET data provides us with information about the required skill level of each task of an occupation. For example, for the job tasks 'Persuading others to change their minds or behaviour', the O*NET gives us information about the *level* of persuasion needed in the given occupation, ranging from a score of 1 to 7, given that the task is required in the first place. In this particular example, the skill level of a score of 2 corresponds to 'Solicit donations for a charity', a score of 4 corresponds to 'Convince a supervisor to purchase a new copy machine' and a score of 6 corresponds to 'Change the opinion of the jury in a complex legal case'. Thus, in addition to being able to measure the angle between two vectors representing occupations so as to get a measure of distance, we can also compare the length of the vectors, so as to get a measure of skill level. In other words, we can study whether once someone has moved employers, they have moved on to tasks that more difficult than what they did before or easier than what they did before. Overall, we find that a one percentage increase in unemployment leads to a decrease in the change of task difficulty of the job. The previous result is primarily driven by individuals being less likely to move to a job with more demanding tasks levels than what they did before, which we interpret as a decrease in up-skilling.

To implement this research we have extended the concept of occupational distance to UK data - previously it has only been studied for the US and Germany. We use CASCOT, a software developed by Jones and Elias (2004) at the University of Warwick to create a working dataset of task distances for UK occupations. To the best of our knowledge, up until now UK datasets did not have task information for occupational categories. Extending the task concepts to UK data allows us to study the effect of the 2008 financial crisis on the task content of transitions for a country other than the US, since Germany did not experience the same increase in unemployment during the given period of study.

A recurring debate within the study of the effect of business cycles is whether they have a sullying or cleansing effect on the labour market. In one line of argument, the frictions that accumulate during expansions are 'cleansed' during recessions by the speeding up of the process of reallocation of workers (e.g. Lilien (1982); Mortensen and Pissarides (1994); Jaimovich and Siu (2014)). An alternative view, put forward by Barlevy (2002), is that since employment-to-employment (E2E) transitions are pro-cyclical it is during economic expansions and not during recessions that labour reallocates better. Thus, in the second view, recessions have a 'sullying' effect on worker reallocation. The evidence on 1-digit occupational moves for the UK by Carrillo-Tudela et al. (2016) is in line with Barlevy (2002). They find that recessions have a sullying rather than cleansing effect since they prevent workers from changing 1-digit occupations at a wage gain. While we do not directly study wages, our approach allows us to say something about the effect of the recession on the realisation of riskier hires and the extent of job-related knowledge accumulation. We find that during recessions new hires tend to move to similar occupations to those they were doing before and they are also less likely to be taking up more challenging tasks, relative to good economic conditions, which is in line with the conclusion that recessions have a sullying effect job transitions.

The rest of the paper is organised as follows: section 3.2 describes the data used. Section 3.3 provides an overview of the measures used to ascertain occupational distance in terms of tasks and task difficulty. Section 3.4 details the methodology behind our reduced form estimation. In section 3.5 we present the results. Finally, section 3.6 concludes with some avenues for future research.

3.2 Data

We use the UK Quarterly Labour Force Surve (LFS) for the years 1997q1-2016q2, which we match to the US O*NET, a dictionary of the task content of occupations. Our aim is to obtain a detailed task profile for each occupation and to subsequently measure the distance between different occupations based on task similarity.

3.2.1 UK Labour Force Survey (LFS)

In the LFS the respondents are followed over two or five quarters. Ideally, we would have used the five quarter data since we would have a better longitudinal sample - however, it is much smaller compared to the two quarter data and raises concerns over attrition bias. As soon as individuals change address in the LFS, they are dropped from the longitudinal sample, which could introduce bias since the individuals that change address are unlikely to be randomly selected over longer periods of time. Since, we are primarily interested in individuals' job transitions, we are able to use the LFS 2Q and focus on E2E transitions only. This is the reason that we do not have information on EUE transitions, i.e. job transitions with a spell of unemployment of 3 months or longer. The survey contains information on individuals' employment status, their employment SOC code, employer tenure, gender, education, reasons for leaving their last job, methods of searching for new jobs, type of work contract (permanent or temporary) and type of employment (employed or self-empolyed). The series are weighted using census population weights provided by the Office for National Statistics (ONS).

In our sample of study we focus on individuals who have experienced a job transition between the first and second quarters that we observe them. In practice, this is achieved by limiting the sample to those individuals that are employed in both quarters of observation, as well as conditioning on having worked for fewer than 2 months with their current employer in the their second quarter of observation. The latter restriction means that we are capturing those who have made an immediate transition from one to the next job or with a minimal period of unemployment in between (less than a month). Excluding transitions that have larger spells of unemployment in between does mean that we have an incomplete picture of hiring - nevertheless, E2E transitions do cover close to 50% of new hires in the UK over the period studied.[1]

Harmonisation of SOC codes in the UK LFS

Over the period of study, the LFS modified its occupational categories twice. One set of occupational definitions runs from 1997q1-2000q4, the second from 2001q2-2010q4, and the third from 2011q1-2016q2. The codes were updated periodically to account for changing requirements within SOC occupation classifications. Figure A.1, in Appendix C, shows a mapping of the SOC1990 to SOC2000 and the SOC2000 to SOC2010, which highlights the changing SOC classifications over time.[2] Between

[1]Author's calculations and similar in magnitude to Carrillo-Tudela et al. (2014).

[2]The Y-axis represents SOC codes at the most dis-aggregated level. The x-axis marks the three points in time when there was a change in SOC code classification, in the 1990s (SOC90), the 2000s

the 1990s and 2000s there was a move towards adopting 4-digit codes, instead of the existing 3-digit codes used in the 1990s. The move from the 1990s to the 2000s involved splitting up occupations that were previously under the same code into a greater number of classifications. The move from the SOC2000 to SOC2010 involved a major re-organisation of occupations within the codes. In the latter recoding, several codes split into finer occupations in the 2010s, while other codes disappeared, highlighting the redundancy of certain occupations over time.

Since the SOC classifications are integral in the mapping to task data, the change in definitions could lead to spurious results. For robustness, we explore a number of different approaches for harmonising the series across time. Previous literature uses the minimum common denominator of occupational codes and applies it to the entirety of the series. The main idea of the approach is as follows: if a SOC2000 code split into two SOC2010 codes, code the two separate SOC2010 codes as one single occupation for the whole series. A similar approach has been used by Dorn (2009) for the US Current Population Survey. Unfortunately, this harmonising technique is not useful for us due to the fact that the mapping between SOC code crosswalks is many-to-many, and after repeated rounds of harmonisation our sample of different occupations is reduced to 70 from the original 352.[3] To overcome this problem we utilise a tool developed by Jones and Elias (2004) at the Warwick Institute For Employment Research, CASCOT (Computer-Assisted Structured Coding Tool).[4] CASCOT is a computer program designed to make a semantic match between occupational titles and standard occupational codes. Using CASCOT, we are able to exploit the data already available in the US O*NET dictionary of tasks in order to classify the task content of UK occupational codes. This mapping is performed by comparing text

(SOC2000) and the 2010s (SOC2010).

[3]More details about why this procedure does not work can be found in Appendix 3.6.

[4]More information available at http://www2.warwick.ac.uk/fac/soc/ier/software/cascot/

descriptions of UK SOC2010 occupations to text descriptions of O*NET occupations for the 2000s and the 2010s, and DOT occupations in the 1990s. It creates a task mapping that is internally consistent for the 1990s, the 2000s and the 2010s, without the need to find matching 2010 codes which preserves the contemporaneous task profile of occupations. After the application of CASCOT, the problem is reduced to a series of visible breaks in the data at the time when the different SOC codes where introduced. To overcome the destabilising effect of the breaks in the analysis, we control for them by a adding a set of macro dummies to the regression.

As a further robustness check we use a simple averaging process, which converts SOC1990 and SOC2000 codes into their matching SOC2010 codes. This works as follows: if a SOC2000 code split into two SOC2010 codes according to the definitions provided by the SOC (as shown in figure A.1), take a simple unweighted average of the task vectors associated with the two SOC2010 codes. Results are qualitatively unchanged by using this different measure.

3.2.2 Occupational transitions over time: the years post-2010 in the LFS

Looking at the series from 2010-2016, we observe an unusual drop in the number of transitions in the early 2010s. This drop covers 6 quarters from 2011q1 - 2012q2. Figure 3.1 plots the estimated probability of career change at the 1-, 2-, 3-, or 4-digit level. Following Carrillo-Tudela et al. (2016), the probability of career change at the k-digit (k=1,2,3,4) is estimated as:

$$\text{Prob Career Change}^k = \frac{E2E_m^k}{E2E_s^k + E2E_m^k},$$

where m refers to *movers*, individuals who changed both employed and also changed their k-digit occupation; s refers to *stayers*, individuals who changed their employer but did not change their k-digit occupation. Thus $E2E_m^k$ is the number of individuals that changed employers and moved k-digit occupation; $E2E_s^k$ is the number of individuals that changed employers and did not move their k-digit occupation. For example, an Economist is in SOC 2 at the one-digit level. If she changed occupations to become a Florist (SOC 5 at the one-digit level), this would be recorded as in $E2E_m^1$. If, however, she became a management consultant (SOC 2), this would be recorded as $E2E_s^1$.

Figure 3.1 clearly shows that the drop in the series occurs at all occupation classification levels from least (1) to most (4) granular. The bottom line is calculated based on 1-digit occupational transition, the 2nd from the bottom on 2-digit transitions and so on. At the time of writing, previous papers using the UK LFS to study occupational transitions stop the analysis in 2010, just before the latest (2010) SOC code change was introduced. We look at the probabilities of career change at the 1-digit, 2-digit, 3-digit and 4-digit level. Up until 2010, the 1-digit data follows a similar pattern to Carrillo-Tudela et al. (2016). Extending the series beyond the 2010s, using 2010-denominated SOC codes, we see that the sharp drop in the probability of changing careers is present in all different digit denominations for a period of six quarters, i.e. from 2011q1 to 2012q2.

It seems clear that this is not a real phenomenon, but a data anomaly.[5] For this reason, we choose to exclude these six quarters from our analysis. A further note of interest is that the LFS does not provide SOC codes for quarter 2000q1, i.e. the year of the move between SOC1990 and SOC2000. We also exclude that quarter for

[5]Our suspicions were raised by the provision of a probabilistic matching of SOC2000 and SOC2010 codes by the LFS, which is only available from 2012q2 onwards, while the official switch from SOC2000 and SOC2010 happened in 2011q1. A series of emails with the UK Data Service confirmed the existence of a mistake in the coding of transitions over these six quarters which, at the time of writing, has not yet been fixed.

our analysis since we cannot obtain any task information.

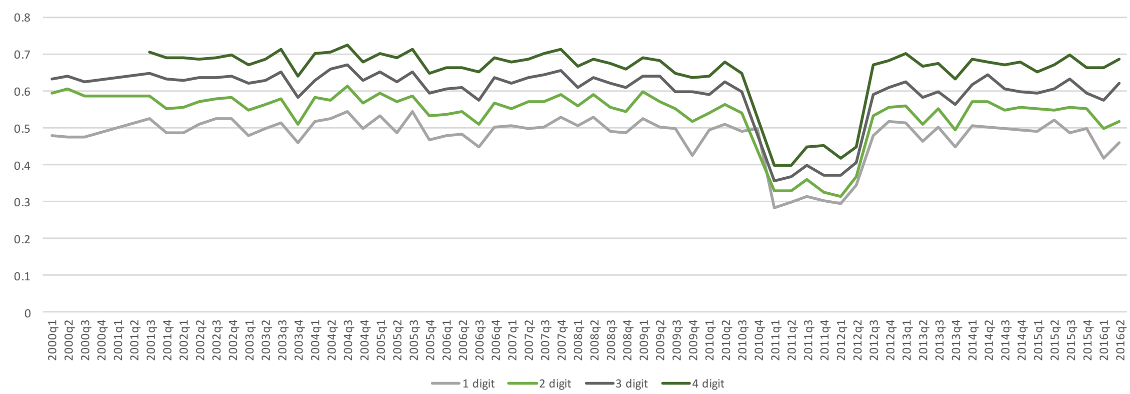


Figure 3.1: Probability of Career Change at 1-,2-,3- and 4-digit

(Probability of career change as estimated as the ratio of E2E movers that changed a) 1-digit (light grey/bottom line), b) 2-digit (light green/ 3rd line) , c) 3-digit (dark grey/ 2nd line), d)4-digit (dark green/ top line) occupation to those E2E that stayed within the respective occupational digit.)

3.2.3 US O*NET

The U.S Department for Labor's O*NET dataset provides us with a detailed picture of the tasks that are used in occupations in the US. The O*NET contains task profiles for 974 occupations, which can then be mapped onto the 374 SOC2010 occupations of the UK LFS.[6] As discussed above, the mapping between O*NET and SOC codes is completed using CASCOT. As can be seen from the number of US and UK occupational categories, the mapping is not one-to-one, but one-to-many. In order to get a single task vector for each SOC code, we use a confidence-weighted average over all matching O*NET occupations, where the confidence weights are provided by the CASCOT software. Each O*NET occupation has scores for each of the 147 tasks in terms of the level of a given skill needed to perform a job (possible scores are in the range 0-7) and the importance of that skill in that occupation

[6]There are 374 SOC 2010 occupations. The number is 352 for 1990s SOC codes and 372 for 2000s SOC codes.

Figure 3.2: Example of mapping the SOC2010 to the O*NET

SOC2010	Description	Oral Comprehension
2425	Actuary	4.81
	Adviser, economic	
	Adviser, statistical	
	Analyst, campaign	
	Analyst, economic	
	Analyst, political	
	Analyst, quantitative	
	Analyst, statistical	
	Analyst, web	
	Assistant, actuarial	
	Assistant, economic	
	Assistant, statistical	
	Bioinformatician	
	Consultant, actuarial	
	Consultant, economic	
	Consultant, statistical	
	Controller, economics	
	Controller, statistical	
	Demographer	
	Economist	

O*NET	Description	Oral Comprehension
15-2041.00	Statisticians	5.12
19-3011.00	Economists	4.75
15-2011.00	Actuaries	4.5
15-2041.01	Biostatisticians	5.12
15-2021.00	Mathematicians	5.25
43-9111.00	Statistical Assistants	4.12
	Average	4.81

(The SOC2010 code that covers occupation 'Economist' is 2425 and also covers a number of other occupations, including Actuary and Bioinformatician. Code 2425 maps to multiple O*NET occupations. Taking an average over all of the Oral Comprehension scores for the different O*NET occupations gives a score for the SOC2010 code.)

(possible scores are in the range 0-5). Figure 3.2 shows a simple example of how the mapping and averaging process works. Taking the example of the SOC2010 code that covers occupation 'Economist' (left panel of Figure 3.2), we see that code 2425 covers a number of occupations. Suppose we are interested in seeing the difficulty level of the task 'Oral Comprehension' for 2425. We take an average over all of the 'Oral Comprehension' scores for the different O*NET matches provided by CASCOT (right panel of Figure 3.2) and obtain a single score (4.81) for 'Oral Comprehension' for the SOC code 2425. We then repeat this procedure for all 147 available tasks and for each SOC code.

3.3 Measuring occupational distance

Characterising an occupation as a vector of tasks is a relatively recent practice in the literature studying job transitions, but is becoming increasingly well-used thanks to better data. Among applied papers, Poletaev and Robinson (2008) are one of the first to map occupational titles to tasks from the US Dictionary for Occupational Titles. Using factor analysis, they group the tasks into four major categories and subsequently rank them by the intensity that they are used in each occupation. They study occupational switches for displaced workers, which they define as the situation when the new occupation employs the previous occupation's 'main skill' with much lower or much higher intensity. Using this definition of occupational moves, they find that wage losses are closely associated with switching skill portfolio, in particular a decrease in the skills. In a follow-up paper, Robinson (2018) uses Euclidean distance between occupations and finds that the mean distance in occupational mobility following displacement declined in the US in the 1980s and 1990s. He also finds that wage losses following displacement are accompanied by downward shifts in the skill portfolio. Our own paper differs from the previous two in that we focus on the change of tasks over the entire population, rather than displaced workers, and we explicitly study the effect of the business cycle on the distance and direction of moves.

Gathmann and Schönberg (2010) also construct a measure of occupational distance based on tasks, which we use in this paper. Using German administrative data, they find that individuals tend to switch to occupations with similar task requirements, and task distance of occupational moves tends to decrease over time. Our own paper differs from in three ways: first, rather than studying the stylised facts of longitudinal occupational moves, we focus on cohorts and study how the task distance as well as the direction of skill of moves changes when a cohort is hit by a recession. Second, rather than using US or German data, we generate a working dataset incorporating a mapping between O*NET tasks and UK occupations within the UK Labour Force Survey [7]. Using UK data allows us to dive into the effects of the recession, since unemployment did significantly rise for the UK during the 2008 financial crisis, while it did not in Germany. Finally, we augment the measure provided by Gathmann and Schönberg (2010) to include not only occupational distance in terms of tasks, but also the direction of the move in terms of the overall skill level.

Contemporaneously, Cortes and Gallipoli (2017) also use the concept of task distance which we use here, but within a different context. Instead of taking the task distance at face value, they interpret it as the cost of occupational mobility. The main idea is that the larger the task distance between two occupations, they greater the cost of moving from one to the other occupation and, as such, the smaller the ratio of movers to stayers. They borrow a gravity model from the trade literature, where job-to-job flows are aggregated at the 2-digit level and are assumed to behave similar to bilateral trade. The traditional geographical distance is replaced with the task distance, while destination and origin country fixed effects are now destination and origin 2-digit occupational fixed effects. Thus, their analysis is aggregated at the occupational level, and they find that the ratio of movers to stayers is negatively affected by greater task distance. Our approach is different in that we want to understand the effect of business cycles on the distance of occupational moves at the individual level.

3.3.1 Task Distance

To measure the task distance between two occupations we use the measure of angular separation of Gathmann and Schönberg (2010), a measure which has also been used

[7]The mapping of O*NET tasks and UK occupational codes (SOC codes) is available from the CASCOT software developed by the University of Warwick

in the innovation literature (Jaffe (1986)). The measure is as follows:

$$\text{Task Distance}_{o,o'} = 1 - \frac{\overbrace{\sum_{t=1}^{T}(q_{t,o} \times q_{t,o'})}^{A}}{\underbrace{\left[(\sum_{t=1}^{T} q_{t,o}^2) \times (\sum_{t=1}^{T} q_{t,o'}^2)\right]^{\frac{1}{2}}}_{\text{B}}} \in [0,1] \tag{3.1}$$

where o, o' is a pair of different occupations, t is the index of the task, $q_{t,o}$ represents the task difficulty of a task t for occupation o and T is the number of tasks. The measure defines the distance between two occupations as one minus the cosine angle between their positions in vector space. Intuitively, the task distance between a set of occupations o and o' are compared by measuring the angle between their respective vectors. The measure varies between $[0, 1]$. It is equal to 0 for jobs that use identical task requirements, i.e. $\frac{A}{B} = 1 \implies A = B$. It is equal to 1 if two jobs use entirely different tasks, i.e. $A = 0$. It will be closer to 0 the more overlap there is in the tasks of two jobs.

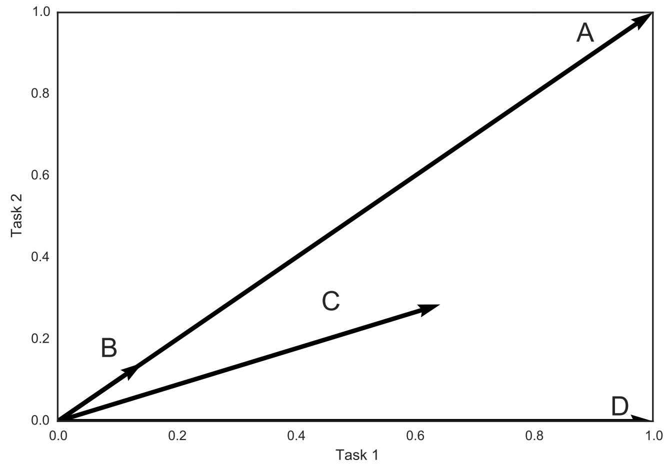
3.3.2 Change in Task Difficulty

The task distance measure does not take into account the length of the vector. In our context, the longer the job vector, the harder the task requirements of the job. When an individual moves to a job with a longer vector, they experience a positive move which we call up-skilling, since the tasks they have to perform are of higher level relative to their old job. If the individual moves to a job with a shorter vector, they de-skill since they now do tasks of lower complexity than before. To capture the degree of up- or de-skilling between occupations, we propose the measure 'ΔTask Difficulty$_{o',o}$' which takes into account the differences in magnitude (length) between two vectors:

$$\Delta\text{Task Difficulty}_{o',o} = \left[\underbrace{\left[\sum_{t=1}^{T} (q_{t,o'}^2) \right]^{\frac{1}{2}}}_{C} - \underbrace{\left[\sum_{t=1}^{T} (q_{t,o}^2) \right]^{\frac{1}{2}}}_{D} \right] / \sqrt{T} \in [-1, 1] \tag{3.2}$$

where the variable names have the same interpretation as in Equation 3.1. Equation 3.2 calculates the difference in the length of two occupation task vectors. Element C gives the length of the task vector for second job and element D for the first job the individual is observed in. The total difference is divided by $\sqrt{T}$ to normalise the outcomes between $[-1, 1]$. If $C > D$, then $\Delta\text{Task Difficulty}_{o',o} > 0$ and we interpret it as an up-skilling move, since the task requirement of the old job were lower than the ones of the new job. If on the other hand $C < D$, then $\Delta\text{Task Difficulty}_{o',o} < 0$, and we have a de-skilling move. In theory an outcome of 0 means two occupations are equally skilled in every task, in practice we don't get perfect zero scores. Thus, negative values will be associated with de-skilling and positive values with up-skilling. The measure is also symmetric, i.e. $\Delta\text{Task Difficulty}_{o',o} = -1 * \Delta\text{Task Difficulty}_{o,o'}$.

Figure 3.3 shows an example in which there are a total of five different occupations (A, B, C, D and E) which comprise two tasks, task 1 and task 2. Moving from occupation A, which is highly skilled in task 1 and task 2, to B, which is lower skilled both tasks gives an angular separation of 0, since the tasks are still used in the same proportion. The $\Delta\text{Task Difficulty}_{o',o}$ of -0.607 reflects the fact that occupation B is much lower skilled than A. Moving from occupation C to A represents both a change in tasks and up-skilling, whereas the change in tasks from A to D constitutes de-skilling. Finally, moving from and to the same occupation A results in zeros for both measures.



Occupation move	Task Distance$_{o,o'}$	ΔTask Difficulty$_{o',o}$
A $\rightarrow$ B	0.0	-0.800
C $\rightarrow$ A	0.067	0.355
A $\rightarrow$ D	0.423	-0.292
A $\rightarrow$ A	0.0	0.0

Figure 3.3: An example of Angular Separation and Skill Score with 2 tasks and 5 occupations

3.3.3 Discussion of the measures

Using the above two measures allows us to take advantage of the rich information available in O*NET to better understand the knowledge content of moves and how it might be affected by recessions. Nevertheless, the measures are not perfect and may be exposed to measurement error due to the original structure of the O*NET difficulty scoring system.

One of the drawbacks of the difficulty scoring for each task is that it may not be comparable across different tasks. For example, level 2 in the task 'Oral Comprehension' may not be comparable to level 2 in the task 'Mathematical Reasoning'. Our measures treat all tasks as symmetric in their difficulty, but one could argue that certain tasks like ‘Science’ or ‘Mathematics’ are in fact graduate tasks, whose level 1 is already much more difficult than level 1 ‘Oral Comprehension’. This is a valid worry - however, only a very small proportion of the 147 available tasks could be categorised as strictly high level tasks and since all occupations have at least 39 tasks from which to calculate a measure, the danger for bias is small.

A further drawback of the difficulty scoring system of O*NET, which again is not controlled for by our measures, is that the scoring system conflates the difficulty level of a task with how often one does a task. For example, if the task ‘Oral comprehension’ gets a score of 0 in the difficulty scale for a given SOC code, it means that the task is not used at all in that occupation. However, if that task gets a score of 4 in a different SOC code, it means that it is used, but we don’t know how often. Thus, a score of 0 for a task is a comment on frequency of use, while a score greater than zero is a comment on difficulty level but not frequency of use. Ideally, we would have preferred to have information both on the difficulty level of each task and on frequency of use, so as to weigh tasks by their importance. Since we lack this information, all tasks used in an occupation are equally weighted in terms of use frequency and tasks not used get a weight of 0.

3.3.4 Evolution of Task Distance and Change in Task Difficulty between 1997q1-2016q3

Figures 3.4 and 3.5 show Task Distance and ΔTask Difficulty$_{o',o}$ averaged within quarters over the period 1997q1-2016q3. The solid lines in each of the figures are the raw unadjusted series, which display 2 structural breaks created by the different definitions of SOC codes between the 1990s, 2000s and 2010s as discussed in section 3.2.1. As explained in 3.2.2, we have had to exclude data from 2001q1 due to missing occupational information, as well as data from between 2011q1-2012q2 due to a coding mistake in the raw data. The dotted lines show the series after adjusting for the structural breaks. The adjustment is achieved by using a dummy to shift the mean of the series in the 1990s and the 2010s in line with the mean in the 2000s, which we use as our reference category. In our estimations we control for the structural breaks by adding a set of dummies for each decade, using the 2000s as our reference category as well.

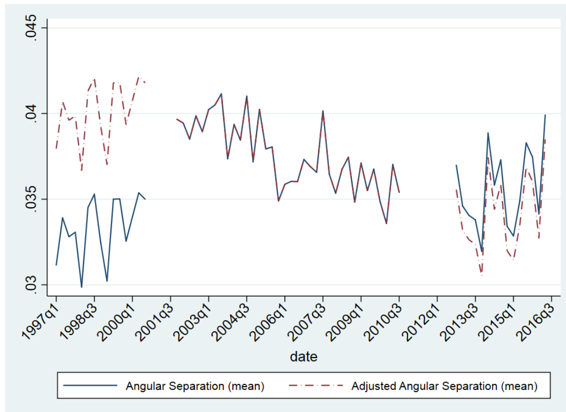


Figure 3.4: Task Distance averaged within quarters, with and without adjustment

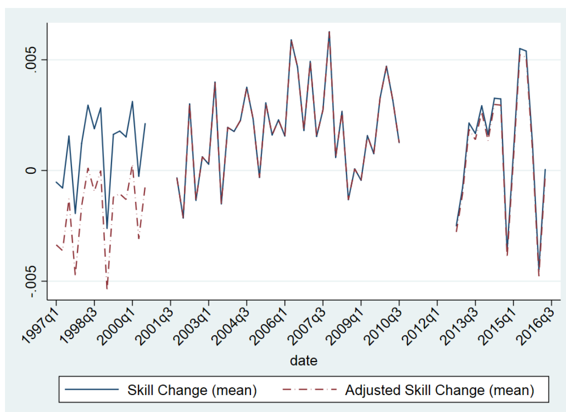


Figure 3.5: Change in Task Difficulty averaged within quarters, with and without adjustment

Figure 3.4 shows the evolution of the average task distance over time, weighted by the number of movers, i.e. those who switched both their employer and their tasks. The graph does not count those who switched employers, without switching tasks. For these individuals the task distance and the change in task difficulty is zero since they didn't change their taks. Thus, the graphs show the average task distance and the average change in task difficulty, conditional on having changed tasks. Around 40% of our sample did not change tasks during their employer switch. In the graph, we see that conditional on switching jobs, there was a weak decrease in the task distance over period of 2006q2-2010q4, with a steady rise after 2015.

Figure 3.5 shows the average change in task difficulty over time, weighted by the number of movers, as in Figure 3.4. The series tends to be above zero for the most part, suggesting that when individuals switch, it is usually to go to a job that has slightly higher requirements than what they did before. This finding is in line with previous work on the importance of job transitions in bringing about wage increases - wage increases are likely to be coupled with a more demanding job. Between 2006q2 and 2010q4, when unemployment went up, 'up-skilling' tends to be become slightly weaker, and does not appear to have recovered by 2016q3.

Table 3.2: Summary Statistics for Task Distance and Change in Task Difficulty

	Task Distance	ΔTask Difficulty
Mean	0.039	0.003
SD	0.033	0.041
Min	0.004	-0.178
Max	0.314	0.176

Excluding observations for which Task Distance = 0

3.4 Econometric Model

3.4.1 The Effect of Business Cycles on the Task Distance and Task Difficulty of Occupational Moves

We use a reduced form Tobit model to test for the effect of the business cycle on the size of the task distance of occupational moves and the change in task difficulty. We choose to use a Tobit, since our measure has a large portion of the sample (approximately 40%) censored at zero (i.e. those who change employers but keep the same occupation obtain a zero in our measure of task distance and change in task difficulty). This is a result of a task distance of zero only occurring where an individual changes employers, and hence experiences an E2E transition, but does not change tasks. Below we summarise the reduced form model.

$$y_{it} = \max(0, \beta_1 * agg\_urate_t + \sum_k \beta_k * X_{k,it} + \sum_j \alpha_j Region_j + e_{it}) \tag{3.3}$$

where y_i is the dependent variable, which is either $Task\ Distance_i$ or $|\Delta\, Task\ Difficulty_i|$. Here, i represents individuals, t is time, j are the number of regional dummies and k are the number of individual controls. The variable agg_urate_t is our main independent variable, the aggregate unemployment rate which captures the effects of business cycles on labour markets. $e_i t$ is the error term.

One criticism of the Tobit model is that it doesn't take into account the potential endogeneity of the decision to change tasks. Among individuals who choose to change employers, people are not randomly allocated into doing similar or different tasks. Thus, endogeneity may be a problem since the types of people who will choose to switch occupations may be different in booms and in busts. Another

To test whether the business cycle leads to up-skilling or de-skilling among individuals undertaking an E2E, we use a reduced form Probit model:

$$D_{it} = \alpha + \beta_1 * agg\_urate_t + \sum_k \beta_k * X_{k,ii} + \sum_j \alpha_j Region_j + e_{it} \tag{3.4}$$

where D_i is the dependent variable, which is a dummy equal to 1 if the individual experience an upskill (downskill) during the E2E transition, and equal to 0 if the individual did not experience a change in skills. Here, i represents individuals, t is time, j are the number of regional dummies and k are the number of individual controls.

We add a set of controls commonly found in the literature of occupational transitions. We first add a set of demographic characteristics, namely age and age squared, marital status, gender, level of education.[8] We also add a set of variables related to the individual's previous job: the duration of the previous employment and whether the separation was voluntary/involuntary or related to retirement. We also control whether the previous job was full-time, whether it was permanent and whether the individual was self-employed. Controls for the current job include whether the job is temporary, whether it is part- or full-time, self-employed, and in the public or private sector. The controls related to the type of job (both previous and new) are important since theory predicts that individuals in more precarious situations may be less tied to a formal job ladder career structure and thus may be more likely to take up jobs where previous expertise is not as important, and thus tasks less similar. Finally, we have a set of controls for the method by which the individual searches for new jobs: through a job centre, adverts, direct applications, family/friends, or

[8]We split education into low, medium and high. In the low category we only include individuals with no qualifications whatsoever; in the middle we include those with at least an Entry Level Qualification and at most A levels (a UK pre-requisite for university entry); and in the high we include all those with any qualification above A levels.

some other method including not having searched at all.

We also add a set of controls for structural breaks. As discussed in sections 3.2 and 3.3.4, there are two breaks in the series due to SOC code name changes when the ONS updated the codes between 2000 and 2001 and between 2010 and 2011. We include a set of two dummies to account for these breaks, taking the series in the 2000s as our reference period and adding a set of dummies for each the other periods, i.e. one for before 2001q1 (first SOC code change) and one for after 2012q2 (second SOC change). The rest of the macro controls are a set of dummies marking quarters to control for seasonality as well as a set of regional dummies to capture regional differences within the UK.

Finally, we test for the separate effect of the recession on cognitive and manual tasks. This is achieved by categorising all tasks in the O*NET as cognitive or manual, according to the definitions by Autor et al. (2003).[9]

3.4.2 Interpreting Tobit coefficients

While in an OLS regression the marginal effect is simply $\frac{\partial E(y|\mathbf{x})}{\partial x_j} = \beta_j$, in Tobit the marginal effect can be written as follows:

$$\frac{\partial E(y|\mathbf{x})}{\partial x_j} = \underbrace{P(y>0|\mathbf{x})\frac{\partial E(y|\mathbf{x}, y>0)}{\partial x_j}}_{\text{A}} + \underbrace{E(y|\mathbf{x}, y>0)\frac{\partial P(y>0|\mathbf{x})}{\partial x_j}}_{\text{B}} = \underbrace{P(y>0|\mathbf{x})\beta_j}_{\text{C}}$$

The above definition of the marginal effect for a Tobit was proposed by McDonald and Moffitt (1980). Term A is the change in the dependent variable, y, of those above zero, weighted by the probability of being above the zero limit, while term B is the

[9]Autor et al. (2003) separate tasks into four sub-categories, i.e. cognitive routine, cognitive non-routine, manual routine, manual non-manual. We only separate along the cognitive and manual tasks into routine/non-routine, but we only do it along the cognitive and manual dimension.

the change in the probability of being above zero, weighted by the expected value of y. Using a simple OLS regression would leave A in the error term, leading to bias. It can be shown that this entire expression simplifies to term C, which has a very simple interpretation: it is the marginal effect of x_i on y, weighted by the probability that $y > 0$ conditional on the independent variables.

To get an estimate for term C, we assume a standard normal distribution of the data and we maximise the log-likelihood function of the tobit model w.r.t β and σ^2. This will yield maximum likelihood estimates and assuming that we have specified the model correctly, it will give us consistent and asymptotically efficient estimators for both β and σ^2. We can then use $\hat{\beta}$ and $\hat{\sigma}$ to estimate the function $P(y > 0|\mathbf{x})$. Using the appropriate expression for the the normal distribution, we obtain $\hat{P}(y > 0|\mathbf{x}) = \frac{1}{N}\sum_{i=1}^{N}\Phi(\mathbf{x}_i\hat{\boldsymbol{\beta}}/\hat{\sigma})$, where $\Phi(.)$ is the CDF of a standard normal and N are the number of observations. Thus the marginal effect is estimated as follows:

$$\frac{\partial \hat{E}(y|\mathbf{x})}{\partial x_j} = \underbrace{\frac{1}{N}\sum_{i=1}^{N}\Phi(\mathbf{x}_i\hat{\boldsymbol{\beta}}/\hat{\sigma})}_{\text{APE scale factor}}\hat{\beta}_j$$

Thus, for the purpose of interpretation of marginal effects, all coefficients that appear in the regression tables have to be multiplied by the APE scale factor to obtain the marginal effect.

One of the drawbacks of the Tobit model is that it can be too restrictive in its interpretation. Both the 'participation decision' (i.e. whether the individual chooses to change tasks or not, $y = 0$ versus $y > 0$) and the 'amount decision' (how much the individual chooses to change their tasks, i.e. how much of y if $y > 0$) are governed by a single mechanism. Since the marginal effect on the Tobit is $\frac{\partial E(y|\mathbf{x})}{\partial x_j} = P(y > 0|\mathbf{x})\beta_j$, we cannot distinguish whether the partial effects on $P(y > 0|\mathbf{x})$ and $E(y|\mathbf{x}, y > 0)$

are of different signs.

One way to overcome the above limitation is to use two-part models allowing for different mechanisms for the participation decision (whether the individual changes tasks at all) and the amount decision (how much does the individual change their tasks, once they have decided to change). Possible models are the Truncated Normal Hurdle Model by Cragg (1971) or the Exponential Type II Tobit model, which is special case of the Heckman 2-step estimator.[10] The main difference between the two is on our assumption on whether the 'participation event' and the 'amount decision' are independent of each other. In the Truncated Normal Hurdle Model the assumption is that the two are independent, while in the Exponential Type II Tobit we assume that the two events are correlated. In the latter model, we are faced with a problem of selection since the two events can be correlated. Thus, following the Heckman 2-step procedure, we need to obtain an exclusion restriction for the first stage estimation, calculate the predicted inverse Mills Ratio for each observation, and in the second stage estimate the extent of the change in tasks using the inverse Mills Ratio as a predictor in the model. If the coefficient on the Mills Ratio is not statistically significantly different from zero then we can assume that there isn't selection and use the Normal Hurdle Model. If there is selection on the 'participation decision', then the coefficient on the inverse Mills ratio will be statistically significant.

Using the two-part models requires an exclusion restriction, i.e. an instrument. Currently, the data does not have any obvious candidates for an instrument that would be correlated with the decision to change tasks or not, but not correlated with the amount of task change that ensues.

[10]See the chapter on Exponential Type II Tobit model in Wooldridge (2010).

3.5 Results

3.5.1 Task Distance over the Business Cycle

Table 3.3 details the most basic regression result based on the model specification of equation 3.3. We show that there is a negative correlation between the unemployment rate and Task Distance, in which an increase in the unemployment rate leads to a decrease in Task Distance between two jobs among those switching. We then test the strength of this finding against a set of traditional control variables in the literature for employment transitions, as outlined in equation 3.3. In Table 3.4, columns 1-3 show how the coefficient of interest changes when adding controls (column 'All') and when isolating the cognitive from the manual tasks (2nd and 3rd columns respectively). In the first column, we see that an increase in the unemployment rate of one percentage point leads to a reduction in task distance.[11] We can interpret this effect as evidence suggesting that individuals make much smaller task changes in E2E transitions during recessions, relative during good economic times. Columns 2-3 of table 3.4 detail the effects of recessions on the cognitive and manual components of occupations, respectively. Recessions lower the distance of moves in cognitive occupations by 4.4 and in manual occupations by 8.8, although the latter is not statistically significant. While it would appear that the effects of the recession are more strongly related to cognitive rather than manual task distance, we find that the difference in coefficients is not statistically significant.[12]

Control variables are, for the most part, significant and of the sign predicted by theory and conditioning for individual and job characteristics does not diminish

[11] The exact marginal effect is given by multiplying the coefficient -13.86 times the APE factor, .59 , first column of table 3.4.

[12] Note that because both the Tobit regression and the measures of task and skill change, equations 3.1 and 3.2, are nonlinear we should not expect the coefficients on cognitive and manual changes to add to the overall effect, labeled 'All' in Table 3.4.

the significance of the pro-cyclical task changes. The size of the coefficients on the controls look much smaller than the size of the effect of aggregate unemployment, but it is important to keep in mind that these coefficients are not comparable since the units of measurement are not the same across all coefficients. The unemployment rate is a continuous variable measured in units of percentage points, while almost all other variables are categorical dummies comparing different groups of people.

Table 3.3: The effect of a Recession on the Task Distance of an E2E transition

	Task Distance
agg_urate	-6.62**
	(2.78)
SOC breaks	Yes
Quarter	Yes
Regions	Yes
N	25940
pseudo R^2	0.001

The dependent variable is Task Distance and the independent variable is the aggregate quarterly unemployment rate.

SE in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Overall, the controls show that there is a pattern of larger task moves for those in worse labour conditions, holding other things equal. For example, going from one temporary job to another temporary job ($temp\_contract1 = 1$ and $temp\_contract2 = 1$) leads to a larger task move, relative to going from one permanent to another permanent contract (*temp_contract*1 $= 0$ and *temp_contract2* $= 0$). Furthemore, less educated workers are more likely to make larger moves, relative to the better educated individuals. Going from one part-time job to another part-time job (*ft_job1* $= 0$ and *ft_job2* $= 0$) is also associated with larger task distances, relative to going from full-time to full-time job (*ft_job1* $= 1$ and *ft_job2* $= 1$). Finally, moving from/to a self-employed spell is also associated with larger task moves, relative to moving from one company to another as an employee (*selfEmp1* $= 0$ and *selfEmp2* $= 0$). These results are largely persistent when looking separately at the cognitive distance and the manual distance, with the exception of the effect of education on the distance of manual moves. In the latter case, we find that individuals with the lowest level of education make smaller manual task moves relative to medium skilled individuals. Finally, we also find that the longer an individual spent in their previous occupation (*spell_durat*), the smaller task and skill changes they make, suggesting that individuals become more specialised over a longer tenure and are less willing to take risks with completely new tasks. Assuming that moving to a job with a substantially different task portfolio is a risky decision, it is not unusual to see that those who are in worse position in terms of education and employment security accept jobs with more dissimilar tasks.

Overall, the outcomes of the controls suggest that the more advantaged individuals, in terms of their labour market position, will be making smaller moves. The outlier to the previous interpretation is the coefficient on involuntary separation (*invol*) - we would have a expected a positive and significant coefficient to account for the fact that after an involuntary separation an individual is more likely to accept a job with different task requirements because they might be in higher need of a job. Nevertheless, we do not find a significant effect of involuntary versus voluntary separation on the size of the task move: this can be explained by the nature of our sample, which only includes individuals from E2E transitions, without any recorded unemployment spells in-between.[13] Thus, we are only capturing the outcomes from the 'luckiest' involuntary transitions, those that resulted in a new job almost immediately and hence the individual may not have had to take a job with substantially different tasks. Finally, all methods of searching for a job increase the task and skill distance of occupational moves, relative to not searching.[14]

3.5.2 Change in Task Difficulty over the Business Cycle

We next study whether recessions affect the change in task difficulty, relative to better economic times. We take the absolute value of equation 3.2 and regress it on the unemployment rate and the controls, as outlined in equation 3.4. Columns 4-6 of Table 3.4 show the effect of a recession on the absolute value of the change in task difficulty. In column 4 we that an increase in the unemployment rate leads to a decrease in the change of task difficulty. In other words, individuals make smaller absolute changes in the task difficulty when changing occupations in recessions,relative to good economic times. The effect remains negative when separate cognitive from manual tasks. The signs and significance of the controls are similar to the controls for Task Distance: we see that lower educated individuals in more unstable work situations will tend to experience larger changes in task difficulty, and that all forms of searching for a job lead to increase in the change in task difficulty.

Nevertheless, as can be seen from graph 3.5, the change in task difficulty is not perfectly symmetric between up-skilling and de-skilling moves since most of the time people tend to make 'positive' moves, i.e. they will move to a more demanding job

[13] In theory, these individuals could have experienced an unemployment spell between their two employment spells, but these spells would be less 2 months-long and thus won't be recorded by the LFS, which follows individuals quarterly.

[14] Methods of search are: *job_center*: via a job centre, *Ads*: applied to adverts, *Direct_app*: applied directly to the employers, *family/friend*: asked family or friends, *other_method*: other method of search.

Table 3.4: Tobit Regression Results

	Task Distance			Change Task Difficulty		
	All	Cognitive	Manual	All	Cognitive	Manual
agg_urate	-13.86**	-7.72***	-15.11	-11.78**	-13.89**	-9.36
	(5.75)	(2.65)	(12.87)	(4.66)	(5.73)	(6.45)
male	0.10	-0.01	1.52***	0.33***	0.32***	-0.06
	(0.09)	(0.04)	(0.21)	(0.08)	(0.09)	(0.10)
age	-0.25***	-0.12***	-0.45***	-0.18***	-0.22***	-0.23***
	(0.02)	(0.01)	(0.05)	(0.02)	(0.02)	(0.03)
age_sq	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
married	-0.22**	-0.12**	-0.39*	-0.19**	-0.24**	-0.12
	(0.11)	(0.05)	(0.23)	(0.09)	(0.11)	(0.12)
H_edu	-1.21***	-0.65***	-0.17	-0.80***	-1.12***	-0.99***
	(0.14)	(0.07)	(0.30)	(0.11)	(0.14)	(0.16)
M_edu	-0.41***	-0.25***	0.54**	-0.24**	-0.39***	-0.16
	(0.13)	(0.06)	(0.26)	(0.10)	(0.13)	(0.14)
spell_durat	-0.12***	-0.06***	-0.23***	-0.08***	-0.10***	-0.11***
	(0.02)	(0.01)	(0.04)	(0.02)	(0.02)	(0.02)
ft_job1	-1.18***	-0.48***	-2.44***	-0.84***	-1.05***	-1.22***
	(0.11)	(0.05)	(0.26)	(0.09)	(0.11)	(0.13)
ft_job2	0.24**	0.02	0.74***	-0.13	-0.22*	0.43***
	(0.12)	(0.05)	(0.26)	(0.10)	(0.12)	(0.13)
temp_contract1	0.09	0.05*	0.15	0.08*	0.11**	0.08
	(0.06)	(0.03)	(0.13)	(0.04)	(0.05)	(0.07)
temp_contract2	0.29***	0.12***	0.66***	0.16***	0.21***	0.30***
	(0.06)	(0.03)	(0.11)	(0.05)	(0.06)	(0.06)
public1	-0.28*	-0.15**	-0.37	-0.28**	-0.45***	-0.41***
	(0.14)	(0.06)	(0.31)	(0.11)	(0.14)	(0.16)
public2	0.72***	0.18***	1.31***	0.50***	0.43***	0.57***
	(0.13)	(0.06)	(0.28)	(0.10)	(0.12)	(0.14)
selfEmp1	2.08***	0.93***	3.65***	0.92*	1.44**	2.15***
	(0.66)	(0.30)	(1.41)	(0.48)	(0.59)	(0.72)
selfEmp2	3.59***	1.43***	7.78***	1.62***	2.21***	3.59***
	(0.54)	(0.25)	(1.06)	(0.44)	(0.53)	(0.58)
invol	-0.15	-0.05	-0.60**	-0.12	-0.08	-0.15
	(0.11)	(0.05)	(0.24)	(0.09)	(0.11)	(0.12)
Ads	1.17***	0.50***	2.38***	0.77***	0.97***	1.21***
	(0.11)	(0.05)	(0.25)	(0.09)	(0.11)	(0.12)
Direct_app	0.15	0.10	-0.18	0.33	0.55**	0.08
	(0.25)	(0.12)	(0.54)	(0.20)	(0.25)	(0.27)
family/friend	0.71***	0.41***	0.56	0.34*	0.42*	0.22
	(0.27)	(0.13)	(0.54)	(0.20)	(0.25)	(0.28)
other_method	0.66***	0.36***	1.35***	0.68***	0.81***	0.54**
	(0.23)	(0.11)	(0.49)	(0.18)	(0.23)	(0.25)
break1_00	-0.85***	-0.31***	-2.10***	-0.52***	-0.60***	-0.81***
	(0.10)	(0.05)	(0.22)	(0.08)	(0.10)	(0.11)
break2_10	-0.70	-0.29	-2.07*	-0.24	-0.16	-0.61
	(0.48)	(0.22)	(1.06)	(0.43)	(0.53)	(0.56)
N	25940	25940	25940	25940	25940	25940
APE	.59	.57	.58	.58	.58	.58
pseudo R^2	0.011	0.014	0.008	0.011	0.011	0.009

In the first three columns, the dependent variable is Angular Separation. In the last three, the dependent variable is the Skill Scale.In the second and fifth columns, the dependent variables only measure the distance resulting from Cognitive tasks, while in the third and the sixth they measure it only for Manual tasks. In order to interpret the marginal effect correctly, the coefficient has to be multiplied by the corresponding APE factor. For the first column, a one percentage-point increase in the unemployment rate leads to a -0.12(0.59)=-0.07 decrease in the Angular Separation. This corresponds to about a third of a standard deviation decrease in Angular Separation.

SE in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

than before. Thus, in addition to looking at the absolute value of the change in task difficulty, we break it down to positive and negative moves and how these different types of moves are affected by recessions.

In table 3.5, we further delve into the effect of the recession on the extent of positive and negative changes in task difficulty for E2E transitions. Looking only at the absolute value of ΔTask Difficulty does not tell us anything about the *direction* of change, so in table 3.5 we split the sample into those who experienced a positive and a negative change in their skill level during the transition. The negative and significant coefficient on *agg_urate* in the 4th column of table 3.4 tells us that there is an overall decrease in the change of skill requirements for E2E, yet we do not know whether this decrease is driven by less up-skilling or more de-skilling. We re-formulate the variable ΔTask Difficulty, so as to get an idea of the direction of the effect. We define a dependent variable that is equal to one if ΔTask Difficulty is positive, and equal to 0 if there is no task change. We see that a one percentage point increase in the unemployment rate decreases the probability of observing up-skilling among E2Es (columns 4-6 in table 3.5). At the same time, we do not see any significant effects from de-skilling (columns 1-3). The latter is not so suprising, since as we saw in graph 3.5 moves are not randomly distributed between up- and de-skilling: most of the time, switching one's employer is associated with an up-skill.

We use the same battery of controls as we did for table 3.4. Over the period of the job switch, the observable characteristics that do not change are the age, education, spell duration of previous job, the characteristics of the first job, and the methods of job search. These 'constant' observables have a comparable effect to individuals' propensity to make an up-skill or de-skilling move, similar to what we observed in Table 3.5. This suggests that while we can predict one's propensity to change their job content based on observable characteristics, it is much harder to predict whether a given move will result in an up-skill or de-skill using observables at the time of job 1, meaning that such a change may be more outside of individuals' immediate control. Where we see more difference in the observables between de-skilling and up-skilling moves is when looking at the general characteristics of the 2nd job. Moving from a part-time to a full-time job, is more likely to be associated with a de-skilling move, pointing to someone's need for higher stability. When the individual chooses to move from a permanent to a temporary contract, the individual is more likely to be up-skilling, thus showing stability sacrifice for more challenging and interesting work. When the individual is moving from being an employee to being self-employed, again they are more likely to be up-skilling which shows a trade-off between stability and interest in the work.

3.6 Conclusion

In this paper we study the extent to which the task content of job transitions is sensitive to cyclical fluctuations. We use data from the UK Labour Force Survey to study employment-to-employment transitions and we map individuals' jobs to their task content using the US O*NET dataset, which contains detailed task information for all jobs. Using a measure of distance from the literature we study whether increases in the unemployment rate affect the task content of new hires that come from employment or minimal unemployment (less than a month). We find that in worse economic times, individuals move to jobs that are more similar to what they did before, relative to better economic times when they take larger job content jumps. With the assumption that continuing to do similar day-to-day activities in one's new job is a less risky strategy than taking up a completely different set of tasks, our interpretation of our results is that moves are pro-cyclical in terms of their task content. In other words, keeping constant the reasons for which individuals may

Table 3.5: Probit Regression Results: De-/Up-skilling

	De-Skilling			Up-Skilling		
	All	Cognitive	Manual	All	Cognitive	Manual
agg_urate	-0.70	-0.77	-0.82	-1.86***	-1.77***	-1.66***
	(0.54)	(0.54)	(0.55)	(0.55)	(0.55)	(0.55)
male (d)	0.03***	0.03***	0.02**	0.05***	0.04***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
age	-0.01***	-0.01***	-0.01***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
age_sq	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
married (d)	-0.02**	-0.02**	-0.01	0.01	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
High_edu (d)	-0.11***	-0.11***	-0.11***	-0.10***	-0.09***	-0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Medium_edu (d)	-0.06***	-0.06***	-0.05***	-0.04***	-0.04***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
spell_durat	-0.01***	-0.01***	-0.01***	-0.00*	-0.00***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ft_job1 (d)	-0.11***	-0.10***	-0.05***	-0.06***	-0.07***	-0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ft_job2 (d)	0.06***	0.05***	0.00	-0.00	0.00	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
temp_contract1	0.02***	0.02***	0.01**	-0.00	-0.00	0.01**
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
temp_contract2	0.01	0.00	0.02***	0.04***	0.04***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
publicr1 (d)	-0.01	-0.02	0.01	-0.07***	-0.06***	-0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
public2 (d)	0.03***	0.04***	0.01	0.08***	0.08***	0.10***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
self_employed1 (d)	0.29***	0.29***	0.13**	0.02	-0.00	0.18***
	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)
self_employed2 (d)	0.04	0.02	0.22***	0.35***	0.38***	0.17***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
invol (d)	-0.02**	-0.02	-0.01	0.01	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
job_center (d)	0.05***	0.05***	0.04**	0.05***	0.05**	0.06***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Ads (d)	0.11***	0.12***	0.10***	0.09***	0.09***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Direct_app (d)	0.03	0.02	0.03	0.01	0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
family/friend (d)	0.05**	0.05*	0.07***	0.04*	0.05**	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
other_method (d)	0.07***	0.07***	0.09***	0.07***	0.08***	0.06***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	17625	17625	17625	17738	17738	17738
pseudo R^2	0.043	0.041	0.032	0.033	0.034	0.043
Log lik.	-12037.82	-12075.87	-11714.71	-11772.80	-11739.59	-12104.27

1 In the first three columns, the dependent variable is a dummy equal to one if the individual has a negative change in task difficulty and it is zero if the individual has no change in task difficulty. In the last three, the dependent variable is equal to one if the individual has a positive change in task difficulty and zero if no change. In the second and fifth columns, the dependent variables only measure the change in task difficulty resulting from cognitive tasks, while in the third and the sixth they measure it only for manual tasks. We report marginal effects and standard errors in the parenthesis.

SE in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

want to switch employers, individuals will tend to 'stay put' in terms of their job specialisation during higher unemployment.

We also study the extent to which individuals will tend to change the average difficulty level of their task portfolio when changing employers. We extend the measure of Gathmann and Schönberg (2010) so as to also measure the change in the difficulty level of an individual's task portfolio when moving employers. We find that overall, the level of difficulty of a job's tasks are less likely to change during recessions, conditional on changing employers. More specifically, we observe that individuals are less likely to move to jobs with higher task requirements during recessions.

Together with previous literature on the negative impact of recessions on career and wage progression (e.g. Carrillo-Tudela et al. (2014)), our own results support the hypothesis that recessions have a sullying effect on the labour market. A smaller propensity to expand one's task specialty, together with being less likely to be hired in positions with more difficult task requirements than their previous job, point to the nefarious consequences of recessions on individuals' development and learning - not just to their wages. Switching employers in good times can bring the benefit of being exposed to new tasks and to learn new skills - these benefits of job switching are reduced during recessions.

In forthcoming work, we extend our analysis to the study of the task content of job transitions that include an unemployment spell (EUE) and we analyse the relation between task changes and wage adjustment over the cycle.

Bibliography

AUTOR, D. H., F. LEVY, AND R. J. MURNANE (2003): "The skill content of recent technological change: An empirical exploration," *The Quarterly Journal of Economics*, 118, 1279–1333.

BARLEVY, G. (2002): "The sullying effect of recessions," *The Review of Economic Studies*, 69, 65–96.

CARRILLO-TUDELA, C., B. HOBIJN, P. SHE, AND L. VISSCHERS (2016): "The extent and cyclicality of career changes: Evidence for the U.K." *European Economic Review*, 84, 18 – 41.

CARRILLO-TUDELA, C., B. HOBJIN, AND L. VISSCHERS (2014): "Career changes decline during recessions," *FRBSF Economic Letters 2014-09*, 2–5.

CORTES, G. M. AND G. GALLIPOLI (2017): "The costs of occupational mobility: An aggregate analysis," *Journal of the European Economic Association*, 16, 275–315.

CRAGG, J. G. (1971): "Some statistical models for limited dependent variables with application to the demand for durable goods," *Econometrica: Journal of the Econometric Society*, 829–844.

DEMING, D. AND L. B. KAHN (2018): "Skill requirements across firms and labor markets: Evidence from job postings for professionals," *Journal of Labor Economics*, 36, S337–S369.

Devereux, P. J. (2000): "Task assignment over the business cycle," *Journal of Labor Economics*, 18, 98–124.

Dorn, D. (2009): "Essays on Inequality, Spatial Interaction, and the Demand for Skills," *Thesis, University of St Gallen.*

Gathmann, C. and U. Schönberg (2010): "How General Is Human Capital? A Task-Based Approach," *Journal of Labor Economics*, 28, 1–49.

Jaffe, A. (1986): "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value," *American Economic Review*, 76, 984–1001.

Jaimovich, N. and H. E. Siu (2014): "The trend is the cycle: Job polarization and jobless recoveries," Working Paper 18334, National Bureau of Economic Research.

Jones, R. and P. Elias (2004): "CASCOT: Computer-assisted structured coding tool," *Coventry: Warwick Institute for Employment Research, University of Warwick.*

Lilien, D. M. (1982): "Sectoral Shifts and Cyclical Unemployment," *Journal of Political Economy*, 90, 777–793.

McDonald, J. F. and R. A. Moffitt (1980): "The Uses of Tobit Analysis," *The Review of Economics and Statistics*, 62, 318–321.

Mortensen, D. T. and C. A. Pissarides (1994): "Job creation and job destruction in the theory of unemployment," *The Review of Economic Studies*, 61, 397–415.

Poletaev, M. and C. Robinson (2008): "Human Capital Specificity : Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000," *Journal of Labor Economics*, 26, 387–420.

Robinson, C. (2018): "Occupational Mobility, Occupation Distance, and Specific Human Capital," *Journal of Human Resources*, 53, 513–551.

Summerfield, F. (2017): "Matching Skills and Tasks: Cyclical Fluctuations in the Overqualification of New Hires," *Manuscript, St Francis Xavier University.*

Wooldridge, J. M. (2010): *Econometric analysis of cross section and panel data*, MIT press.

Appendix A

A.1 Using the cognitive components of PIAAC

1.Estimating standard errors for the cognitive components of PIAAC

The skills variables in PIAAC have been sampled using the Jackknife replicate procedure. In practice, this means that when computing the standard errors of the skills variables (i.e. numeracy, literacy and problem solving), measurement error must be taken into account. The standard error for a statistic involving skills variables might be expressed as:

$$
\begin{aligned}
SE_{\theta_\rho} &= \sqrt{(\text{Sampling error})^2 + (\text{Measurement error})^2} \\
&= \sqrt{\left[\sum_{p=1}^{P}\left(f\sum_{r=1}^{R}(\hat{\theta}_{r,p} - \bar{\theta}_{0,P})^2\right)\frac{1}{P}\right] + \left[\left(1+\frac{1}{P}\right)\frac{\sum\limits_{p=1}^{P}(\hat{\theta}_{0,p} - \bar{\theta}_{0,P})^2}{P-1}\right]}
\end{aligned}
$$

where:

R is the number of replicates

P is the number of plausible values $p = (1, ..., P)$

$\bar{\theta}_{0,P} = \frac{\sum\limits_{p=1}^{P}\theta_{0,p}}{P}$

$\hat{\theta}_{r,p}$ represents the statistic estimate r and the pth plausible value

$\hat{\theta}_{0,p}$ represent is the statistic estimate using the final sample weight for the pth plausible value

$\bar{\theta}_{0,P}$ represents the unweighted average of the statistic for each plausible value using the whole sample and the final weight

In the PIAAC data there are 10 plausible values for each of the skills measured (in total 30 plausible values) and a total of 80 replicate weights for each country. So implementing the correct standard errors requires 810 repetitions of computations of the statistic of interest. These calculations can be done quite easily using the user-written Stata command 'repest'.

2.Creating new variables based on the PIAAC cognitive components

A difficulty arises when wishing to create new variables within PIAAC that are derivatives of the skills variables, e.g. the $Mismatch_i$ variable that is used in this paper. Each observation in the PIAAC dataset is not mapped to one literacy skill score, but 10 'possible' literacy scores; or as they are formally called, 10 plausible values. Thus, if we wish to create a new variable that is a direct derivative of the literacy skill scores variables, the new variable must follow the standard error correction rules of the original skills variable. In other words, we have to create 10 plausible values for the new variable using each of the existing plausible values of the skills variables. We also have to name the variables accordingly, so that the 'repest' command is able to recall them correctly when performing the standard error estimations [15].

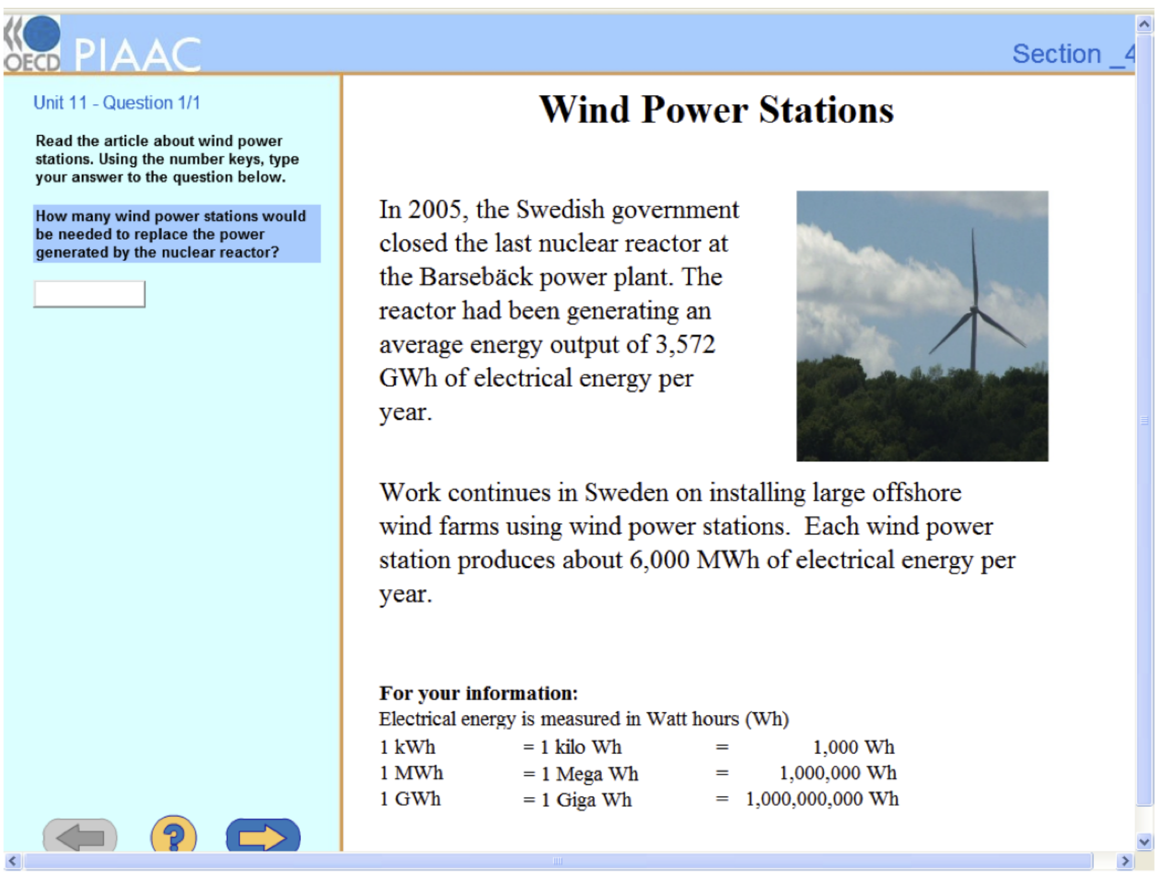
[15] More information on how to name the variables can be found in the Stata helpfile for 'repest'

A2. Examples of the Skills Tests Questions

1.Sample Numeracy Question

This sample item is of medium difficulty and focuses on the following aspects of the numeracy construct:

Content	Quantity and Number
Process	Act upon, use (compute)
Context	Community and Society

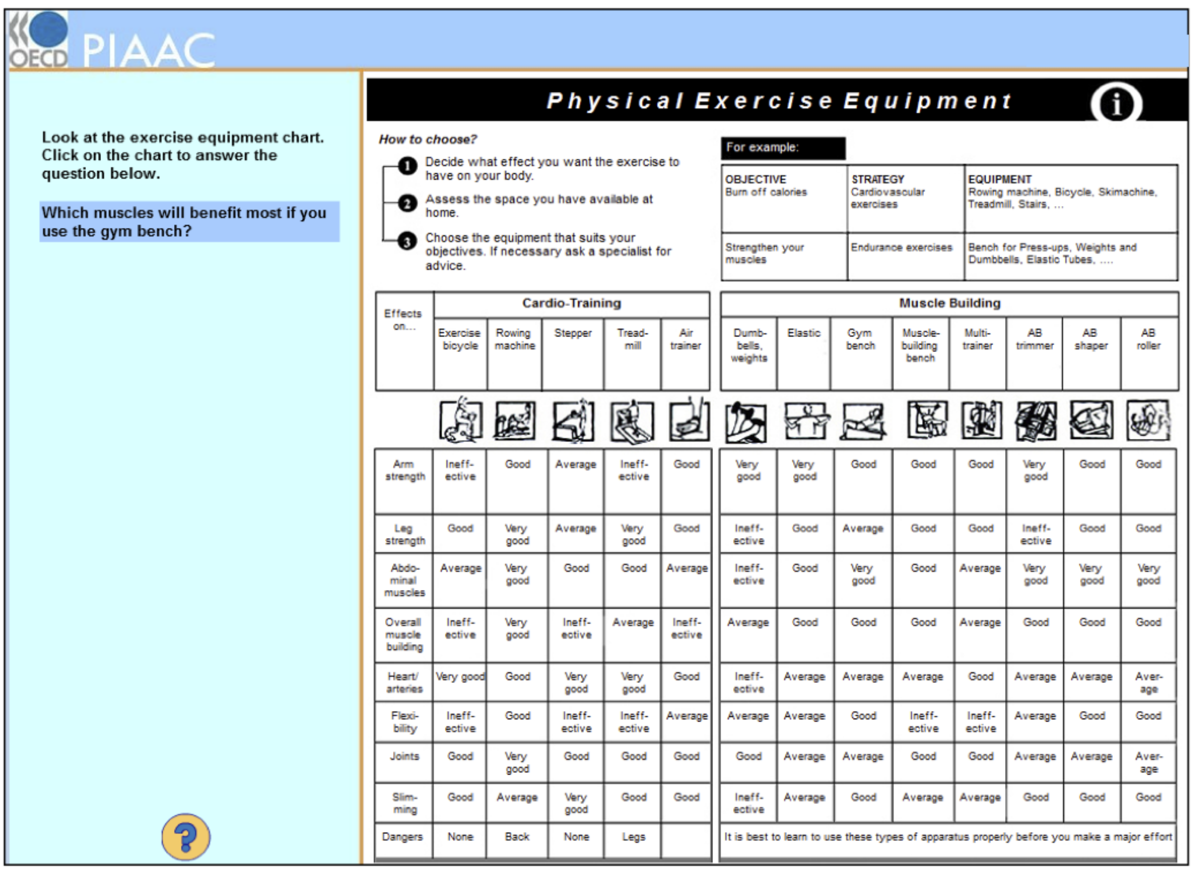


2.Sample Literacy Question

This is a relatively easy item and focuses on the following aspects of the literacy construct:

Cognitive process	Access and identity
Context	Personal
Medium	Print

Respondents answer the question by clicking on the cell in the chart that contains information about exercise equipment. Each of the cells and all of the images are 'clickable' and multiple cells can be selected.



OECD PIAAC

Look at the exercise equipment chart. Click on the chart to answer the question below.

Which muscles will benefit most if you use the gym bench?

Physical Exercise Equipment

How to choose?

1. Decide what effect you want the exercise to have on your body.
2. Assess the space you have available at home.
3. Choose the equipment that suits your objectives. If necessary ask a specialist for advice.

For example:

OBJECTIVE	STRATEGY	EQUIPMENT
Burn off calories	Cardiovascular exercises	Rowing machine, Bicycle, Skimachine, Treadmill, Stairs, ...
Strengthen your muscles	Endurance exercises	Bench for Press-ups, Weights and Dumbbells, Elastic Tubes, ...

Effects on...	Cardio-Training					Muscle Building							
	Exercise bicycle	Rowing machine	Stepper	Tread-mill	Air trainer	Dumb-bells, weights	Elastic	Gym bench	Muscle-building bench	Multi-trainer	AB trimmer	AB shaper	AB roller
Arm strength	Ineff-ective	Good	Average	Ineff-ective	Good	Very good	Very good	Good	Good	Good	Very good	Good	Good
Leg strength	Good	Very good	Average	Very good	Good	Ineff-ective	Good	Average	Good	Good	Ineff-ective	Good	Good
Abdo-minal muscles	Average	Very good	Good	Good	Average	Ineff-ective	Good	Very good	Good	Average	Very good	Very good	Very good
Overall muscle building	Ineff-ective	Very good	Ineff-ective	Average	Ineff-ective	Average	Good	Good	Good	Average	Good	Good	Good
Heart/ arteries	Very good	Good	Very good	Very good	Good	Ineff-ective	Average	Average	Average	Good	Average	Average	Aver-age
Flexi-bility	Ineff-ective	Good	Ineff-ective	Ineff-ective	Average	Average	Average	Good	Ineff-ective	Ineff-ective	Average	Good	Good
Joints	Good	Very good	Good	Good	Good	Good	Average	Average	Good	Good	Average	Average	Aver-age
Slim-ming	Good	Average	Very good	Good	Good	Ineff-ective	Average	Good	Average	Average	Good	Good	Good
Dangers	None	Back	None	Legs		It is best to learn to use these types of apparatus properly before you make a major effort							

Appendix B

B1.Kolmogorov-Smirnov Tests

Since there are 10 plausible values for each individual's skills scores, we perform the KS test for each plausible value separately and subsequently aggregate the results in table 2.5 for easier interpretation. Here are the detailed results, by country, by skill and for each plausible value.

	Belgium			
	Literacy		*Numeracy*	
	D-stat	p-value	D-stat	p-value
1	0.05	0.120	0.03	0.58
2	0.04	0.36	0.03	0.28
3	0.05	0.05	0.04	0.27
4	0.05	0.07	0.04	0.28
5	0.04	0.17	0.03	0.41
6	0.04	0.13	0.03	0.41
7	0.04	0.32	0.03	0.61
8	0.03	0.52	0.04	0.16
9	0.04	0.24	0.03	0.45
10	0.04	0.27	0.03	0.62

	Czech Republic			
	Literacy		*Numeracy*	
	D-stat	p-value	D-stat	p-value
1	0.03	0.49	0.05	0.07
2	0.02	0.94	0.07	0.00
3	0.02	0.90	0.06	0.04
4	0.03	0.53	0.06	0.02
5	0.04	0.19	0.07	0.00
6	0.03	0.74	0.05	0.06
7	0.03	0.68	0.06	0.02
8	0.04	0.32	0.05	0.04
9	0.03	0.68	0.05	0.04
10	0.02	0.87	0.06	0.01

	Denmark			
	Literacy		*Numeracy*	
	D-stat	p-value	D-stat	p-value
1	0.03	0.17	0.06	0.00
2	0.04	0.10	0.05	0.01
3	0.03	0.38	0.06	0.00
4	0.03	0.41	0.06	0.00
5	0.04	0.06	0.07	0.00
6	0.04	0.08	0.05	0.00
7	0.04	0.09	0.05	0.01
8	0.03	0.21	0.06	0.00
9	0.03	0.17	0.06	0.00
10	0.03	0.12	0.05	0.00

	France			
	Literacy		*Numeracy*	
	D-stat	p-value	D-stat	p-value
1	0.07	0.00	0.04	0.11
2	0.07	0.00	0.04	0.19
3	0.06	0.00	0.04	0.07
4	0.05	0.01	0.02	0.64
5	0.07	0.00	0.03	0.41
6	0.07	0.00	0.03	0.46
7	0.06	0.00	0.03	0.30
8	0.05	0.03	0.03	0.28
9	0.06	0.00	0.03	0.61
10	0.06	0.00	0.04	0.16

	Italy			
	Literacy		*Numeracy*	
	D-stat	p-value	D-stat	p-value
1	0.06	0.13	0.04	0.35
2	0.08	0.01	0.07	0.04
3	0.08	0.00	0.05	0.18
4	0.07	0.03	0.05	0.17
5	0.05	0.21	0.04	0.56
6	0.05	0.13	0.05	0.22
7	0.05	0.14	0.05	0.31
8	0.05	0.21	0.05	0.18
9	0.05	0.16	0.05	0.27
10	0.07	0.03	0.05	0.22

	The Netherlands			
	Literacy		*Numeracy*	
	D-stat	p-value	D-stat	p-value
1	0.04	0.11	0.06	0.00
2	0.05	0.05	0.07	0.00
3	0.05	0.04	0.07	0.00
4	0.04	0.14	0.06	0.01
5	0.04	0.19	0.08	0.00
6	0.07	0.00	0.06	0.01
7	0.03	0.26	0.07	0.01
8	0.05	0.07	0.06	0.01
9	0.05	0.03	0.07	0.00
10	0.05	0.08	0.07	0.00

	Poland			
	Literacy		*Numeracy*	
	D-stat	p-value	D-stat	p-value
1	0.04	0.06	0.08	0.00
2	0.04	0.05	0.09	0.00
3	0.04	0.12	0.08	0.00
4	0.03	0.46	0.07	0.00
5	0.03	0.27	0.09	0.00
6	0.02	0.88	0.08	0.00
7	0.04	0.12	0.09	0.00
8	0.03	0.22	0.06	0.00
9	0.03	0.39	0.08	0.00
10	0.03	0.56	0.09	0.00

	Slovakia			
	Literacy		*Numeracy*	
	D-stat	p-value	D-stat	p-value
1	0.03	0.53	0.08	0.00
2	0.03	0.47	0.06	0.01
3	0.02	0.89	0.06	0.04
4	0.02	0.89	0.07	0.00
5	0.04	0.25	0.06	0.04
6	0.03	0.61	0.07	0.00
7	0.03	0.68	0.07	0.00
8	0.03	0.43	0.07	0.00
9	0.03	0.50	0.06	0.01
10	0.03	0.64	0.08	0.00

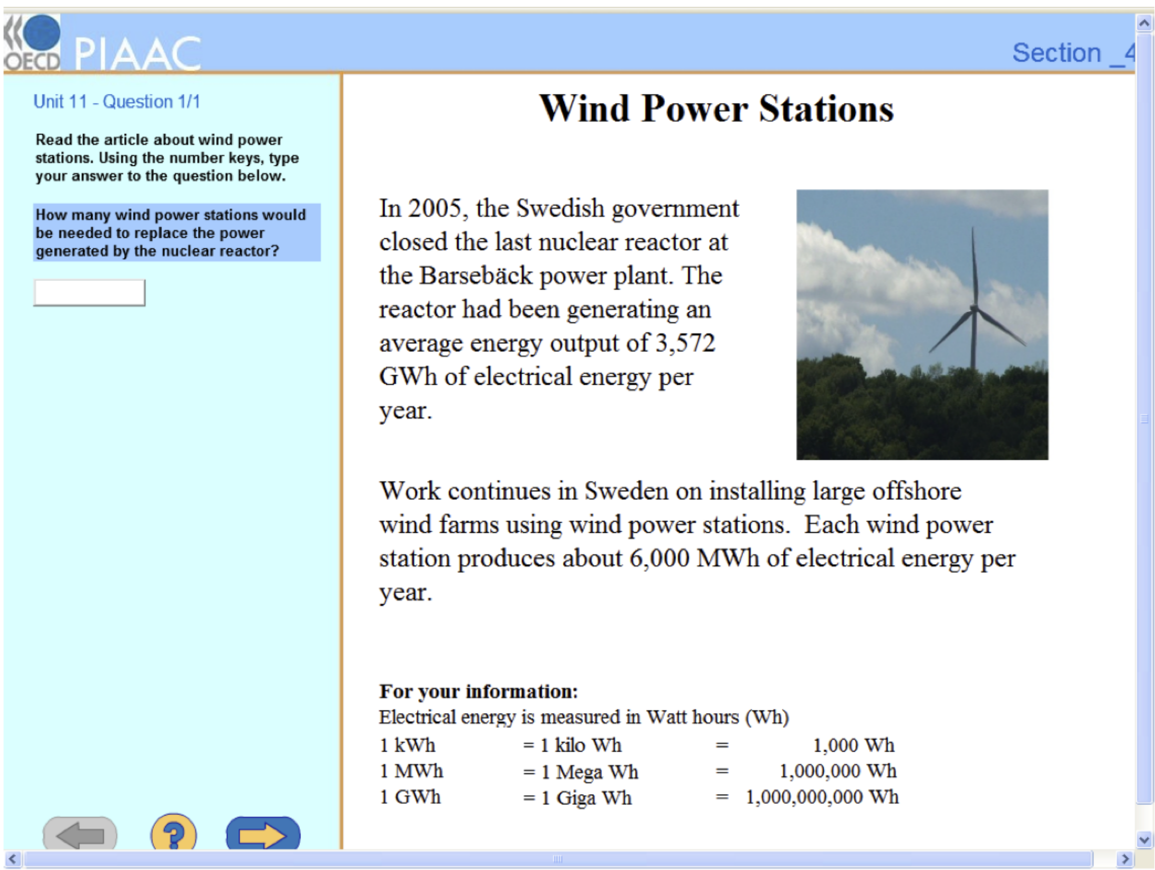
	Spain			
	Literacy		*Numeracy*	
	D-stat	p-value	D-stat	p-value
1	0.03	0.73	0.05	0.03
2	0.03	0.54	0.07	0.00
3	0.04	0.34	0.06	0.04
4	0.03	0.72	0.06	0.01
5	0.03	0.71	0.06	0.02
6	0.04	0.40	0.06	0.02
7	0.02	0.91	0.06	0.04
8	0.03	0.64	0.06	0.02
9	0.03	0.76	0.07	0.01
10	0.04	0.41	0.07	0.01

B2.Examples of Skills Tests from PIAAC

1.Sample Numeracy Question

This sample item is of medium difficulty and focuses on the following aspects of the numeracy construct:

Content	Quantity and Number
Process	Act upon, use (compute)
Context	Community and Society

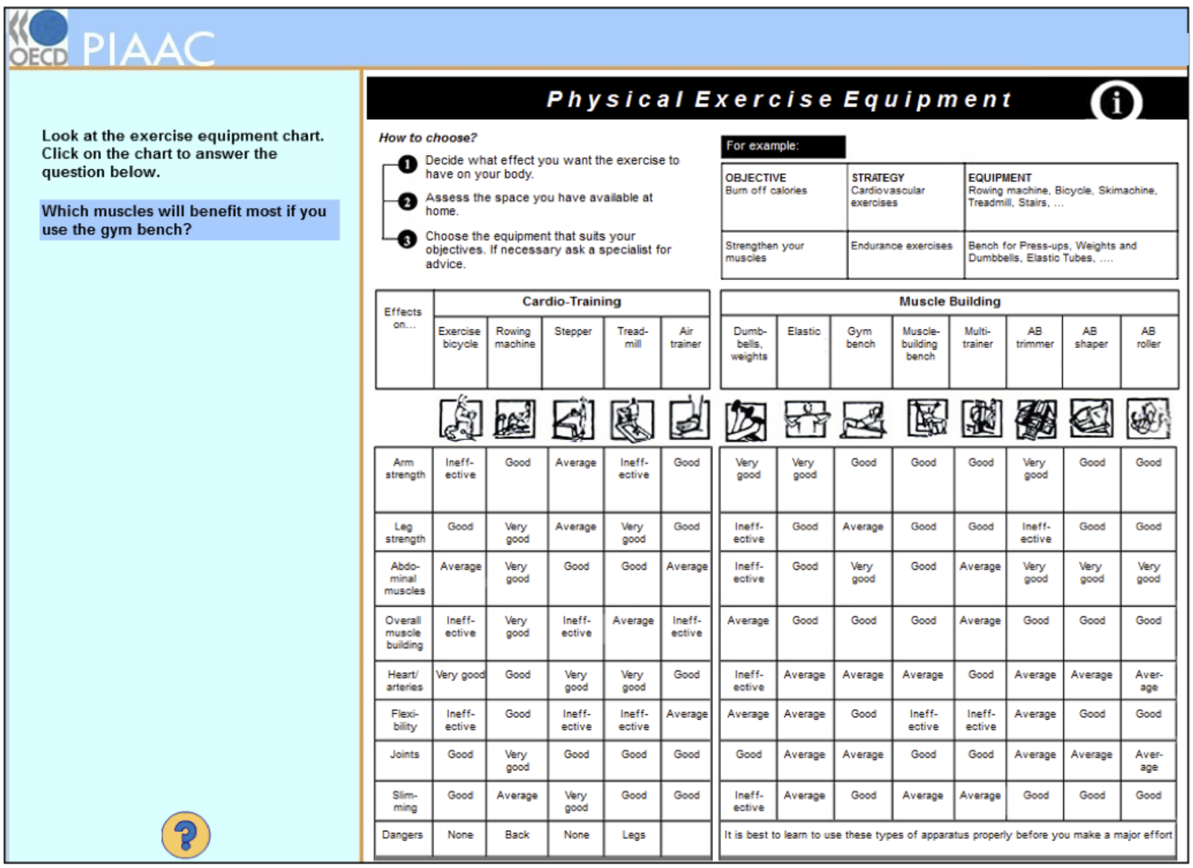


2.Sample Literacy Question

This is a relatively easy item and focuses on the following aspects of the literacy construct:

Cognitive process	Access and identity
Context	Personal
Medium	Print

Respondents answer the question by clicking on the cell in the chart that contains information about exercise equipment. Each of the cells and all of the images are 'clickable' and multiple cells can be selected.


PIAAC

Look at the exercise equipment chart. Click on the chart to answer the question below.

Which muscles will benefit most if you use the gym bench?

Physical Exercise Equipment

How to choose?

1. Decide what effect you want the exercise to have on your body.
2. Assess the space you have available at home.
3. Choose the equipment that suits your objectives. If necessary ask a specialist for advice.

For example:

OBJECTIVE	STRATEGY	EQUIPMENT
Burn off calories	Cardiovascular exercises	Rowing machine, Bicycle, Skimachine, Treadmill, Stairs, ...
Strengthen your muscles	Endurance exercises	Bench for Press-ups, Weights and Dumbbells, Elastic Tubes, ...

Effects on...	Cardio-Training					Muscle Building							
	Exercise bicycle	Rowing machine	Stepper	Tread-mill	Air trainer	Dumb-bells, weights	Elastic	Gym bench	Muscle-building bench	Multi-trainer	AB trimmer	AB shaper	AB roller
Arm strength	Ineff-ective	Good	Average	Ineff-ective	Good	Very good	Very good	Good	Good	Good	Very good	Good	Good
Leg strength	Good	Very good	Average	Very good	Good	Ineff-ective	Good	Average	Good	Good	Ineff-ective	Good	Good
Abdo-minal muscles	Average	Very good	Good	Good	Average	Ineff-ective	Good	Very good	Good	Average	Very good	Very good	Very good
Overall muscle building	Ineff-ective	Very good	Ineff-ective	Average	Ineff-ective	Average	Good	Good	Good	Average	Good	Good	Good
Heart/ arteries	Very good	Good	Very good	Very good	Good	Ineff-ective	Average	Average	Average	Good	Average	Average	Aver-age
Flexi-bility	Ineff-ective	Good	Ineff-ective	Ineff-ective	Average	Average	Average	Good	Ineff-ective	Ineff-ective	Average	Good	Good
Joints	Good	Very good	Good	Good	Good	Good	Average	Average	Good	Good	Average	Average	Aver-age
Slim-ming	Good	Average	Very good	Good	Good	Ineff-ective	Average	Good	Average	Average	Good	Good	Good
Dangers	None	Back	None	Legs		It is best to learn to use these types of apparatus properly before you make a major effort							

Appendix C

C1. OLS results

Table C.1: Robustness: OLS Regression Results

	Angular Separation			Skill Scale		
	All	Cognitive	Manual	All	Cognitive	Manual
agg_urate	-7.92**	-4.73***	-3.35	-7.30**	-7.85**	-3.30
	(-2.16)	(-2.81)	(-0.39)	(-2.40)	(-2.11)	(-0.78)
male	-0.09	-0.10***	0.95***	0.18***	0.11*	-0.25***
	(-1.42)	(-3.25)	(6.72)	(3.43)	(1.74)	(-3.61)
age	-0.17***	-0.09***	-0.29***	-0.13***	-0.15***	-0.15***
	(-10.88)	(-11.80)	(-8.49)	(-10.04)	(-9.82)	(-8.83)
age_sq	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(9.19)	(10.07)	(7.30)	(8.44)	(8.39)	(7.23)
married	-0.13*	-0.08**	-0.20	-0.12**	-0.15**	-0.04
	(-1.94)	(-2.49)	(-1.37)	(-2.29)	(-2.24)	(-0.54)
H_edu	-0.66***	-0.37***	0.80***	-0.40***	-0.57***	-0.40***
	(-6.96)	(-8.56)	(4.06)	(-5.42)	(-6.14)	(-3.84)
M_edu	-0.18**	-0.13***	0.92***	-0.09	-0.15*	0.08
	(-2.08)	(-3.30)	(5.30)	(-1.29)	(-1.74)	(0.83)
spell_durat	-0.07***	-0.04***	-0.13***	-0.05***	-0.06***	-0.06***
	(-6.02)	(-6.60)	(-4.83)	(-4.92)	(-4.82)	(-4.34)
ft_job1	-0.80***	-0.31***	-1.60***	-0.53***	-0.68***	-0.80***
	(-9.94)	(-8.16)	(-8.38)	(-7.83)	(-8.43)	(-8.64)
ft_job2	0.18**	0.01	0.60***	-0.14**	-0.23***	0.35***
	(2.28)	(0.14)	(3.15)	(-2.01)	(-2.74)	(3.78)
temp_contract1	0.04	0.02	0.04	0.04	0.06*	0.03
	(0.96)	(1.17)	(0.40)	(1.41)	(1.67)	(0.54)
temp_contract2	0.19***	0.08***	0.43***	0.09***	0.12***	0.18***
	(5.22)	(4.56)	(6.16)	(2.90)	(3.22)	(4.68)
public1	-0.12	-0.06	-0.07	-0.15**	-0.27***	-0.21**
	(-1.28)	(-1.56)	(-0.33)	(-1.99)	(-2.95)	(-1.99)
public2	0.48***	0.08**	0.78***	0.30***	0.22***	0.32***
	(5.33)	(2.17)	(3.82)	(4.06)	(2.61)	(3.20)
selfEmp1	1.22***	0.52**	1.77*	0.35	0.66*	1.18**
	(2.68)	(2.49)	(1.79)	(1.08)	(1.70)	(2.36)
selfEmp2	2.47***	0.92***	5.28***	0.88***	1.25***	2.37***
	(7.16)	(5.78)	(7.83)	(2.94)	(3.58)	(6.26)
invol	-0.11	-0.03	-0.48***	-0.06	-0.05	-0.10
	(-1.53)	(-0.96)	(-3.08)	(-1.09)	(-0.72)	(-1.31)
Ads	0.65***	0.26***	1.24***	0.37***	0.47***	0.64***
	(8.51)	(7.25)	(7.17)	(6.02)	(6.29)	(7.34)
Direct_app	0.06	0.06	-0.31	0.25*	0.42**	-0.00
	(0.40)	(0.76)	(-0.85)	(1.79)	(2.49)	(-0.01)
family/friend	0.43**	0.27***	0.04	0.12	0.17	-0.03
	(2.32)	(3.01)	(0.10)	(0.95)	(1.04)	(-0.18)
other_method	0.31**	0.19***	0.58*	0.39***	0.44***	0.16
	(2.06)	(2.66)	(1.74)	(3.09)	(2.83)	(0.94)
break1_00	-0.46***	-0.13***	-1.18***	-0.20***	-0.25***	-0.39***
	(-7.24)	(-4.40)	(-8.26)	(-3.85)	(-3.80)	(-5.40)
break2_10	-0.42	-0.16	-1.39**	-0.00	0.05	-0.31
	(-1.42)	(-1.21)	(-2.03)	(-0.01)	(0.15)	(-0.83)
N	25940	25940	25940	25940	25940	25940
R^2	0.047	0.046	0.037	0.042	0.041	0.033

1 In the first three columns, the dependent variable is Angular Separation. In the last three, the dependent variable is the Skill Scale. In the second and fifth columns, the dependent variables only measure the distance resulting from Cognitive tasks, while in the third and the sixth they measure it only for Manual tasks. For the first column, a one percentage-point increase in the unemployment rate leads to a -0.07 decrease in the Angular Separation. This corresponds to about one and a half standard deviations decrease in Angular Separation. SE in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C2. Occupational codes in the UK LFS

Occupational categories in the LFS do not remain constant over time. The UK records up to 4-digit occupational categories in the two-quarter longitudinal LFS, starting with 3-digit codes in 1997 and going up to 4-digit codes from the 2000s onwards[16]. Occupational codes have been through two major re-organisations. Between the 1990s and the 2000s, the LFS disaggregated the codes from 3-digit to 4-digits. The transition in the data is not smooth, in the sense that the dictionary of transitions is not accompanied by a probabilistic mapping between the SOC90 and SOC00. In the data, SOC90 is used up until 2000q4 and SOC00 is used starting from 2001q2. Thus, there is a gap in 2001q1, where all occupational information is missing. Between the 2000s and 2010s, the transition is made easier for the researcher, since in addition to the dictionary of transitions, a probabilistic mapping is provided for 2012q2.

There are several ways to standardise the occupational series over time, so as to be able to make valid comparisons, which are a crucial element in this chapter. The simplest strategy would have been to take the 'minimum common denominator'. For example, if we observe that a single occupation in 1990 splits into two different occupations in 2000, and these in turn split into 3 more occupations in the 2010s, our strategy would have been to use the 1990 codes as a reference category and 'merge' any follow up occupational splits. However, this particular fix would mean that we would lose most of the variation in the data. Out of the 375 SOC2000, only 69 occupations have a one-to-one match with the new SOC2010 codes. The rest of the codes are many-to-many matches. Applying this to the data would mean that all many-to-many matches would end up becoming one single very large occupation, leaving us with a total of only 70 occupations from which to observe angular separation (69 one-to-one matches + the 1 large occupation from the many-to-many matches).

[16]The longitudinal series started in 1992, yet between 1992 and 1997 only 1-digit major occupational codes were recorded. Although 3-digit occupational codes have been recorded for the cross-sectional element of the LFS since 1975, these were not transferred to the longitudinal element before 1997.

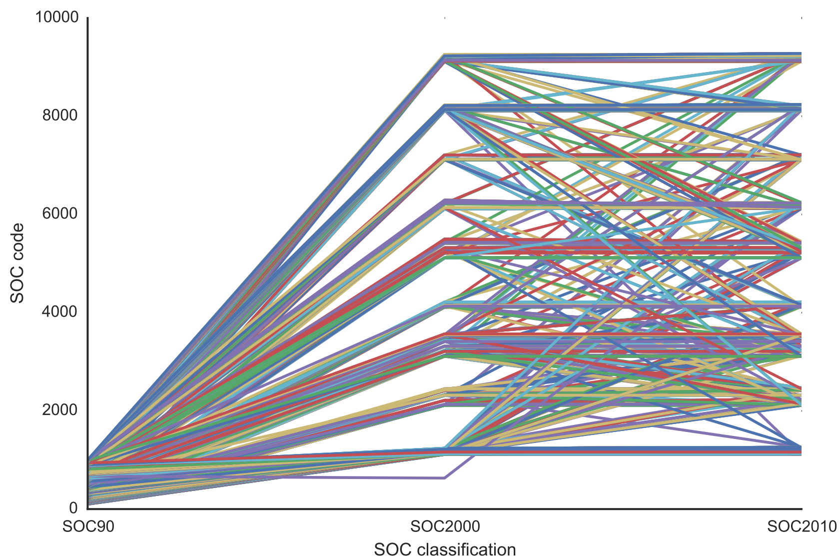


Figure A.1: Mapping between all SOC90, SOC2000 and SOC2010 codes

C3. Summary statistics for E2E transitions

A consideration with the design of our study is that the type of individuals that transition during and outside of recessions are significantly different, leading to our results being driven entirely by differences in composition. In table 1 we outline a set of summary statistics of observable characteristics for the individuals observed during and outside of a recession. The sample of study is made up of individuals experiencing an E2E transition, without any unemployment spells in between.

Most differences in the means of characteristics are not statistically significant - however, there are a number of exceptions. During recessions there are fewer women and fewer highly educated individuals among our sample, while at the same time there are more lower-educated individuals. The duration spell of the previous job also tends to be shorter among those who transition in a recession and there are fewer individuals transitioning after being fired in a recession.

In our regressions, we control for all the variables listed in table 1. While most of them significantly affect the task distance of occupational moves, we see from Table 1 that most are similar for the recession and non-recession samples. This is reassuring, since it suggests that the results are driven by more than compositional effects alone.

Table C.2: Difference in means between E2E during recessions and non-recessions

Variable	No recession	Recession	Diff
Male	0.50	0.49	-0.015**
	(0.00)	(0.00)	(0.006)
age	33.17	33.15	-0.023
	(0.10)	(0.11)	(0.148)
married	0.42	0.43	0.016***
	(0.00)	(0.00)	(0.006)
spell duration (l)	4.31	4.23	-0.076**
	(0.02)	(0.02)	(0.030)
full-time (c)	0.76	0.76	0.007
	(0.00)	(0.00)	(0.005)
temporary job (l)	-0.56	-0.52	0.038
	(0.02)	(0.02)	(0.032)
self-employed (l)	0.08	0.07	-0.005*
	(0.00)	(0.00)	(0.003)
public sector (l)	0.15	0.15	0.003
	(0.00)	(0.00)	(0.004)
high edu	0.33	0.31	-0.019***
	(0.00)	(0.00)	(0.006)
medium edu	0.54	0.55	0.005
	(0.00)	(0.00)	(0.006)
low edu	0.13	0.14	0.013***
	(0.00)	(0.00)	(0.004)
Job search method			
job centre	0.05	0.05	-0.001
	(0.00)	(0.00)	(0.003)
ads	0.17	0.17	-0.004
	(0.00)	(0.00)	(0.005)
direct applications	0.03	0.03	-0.001
	(0.00)	(0.00)	(0.002)
family/friend	0.03	0.03	0.000
	(0.00)	(0.00)	(0.002)
other	0.03	0.04	0.004*
	(0.00)	(0.00)	(0.002)
Reason for leaving			
quit	0.23	0.23	0.008
	(0.00)	(0.00)	(0.005)
fired	0.48	0.47	-0.014**
	(0.00)	(0.00)	(0.006)
other	0.29	0.30	0.005
	(0.00)	(0.00)	(0.006)
N	14330	11771	26101

[1] Significance levels: * < 10% ** < 5% *** < 1%
[2] Standard errors in parentheses
[3] (l) refers to last job; (c) refers to current job.
[4] This table shows the difference in the means of observed characteristics of switchers during recessions and non-recessions. The third column shows the outcome of a difference-in-means test.

C4. Derivation of the Marginal Effect for Tobit

Tobin (1958) shows that for the Tobit model the expected value of y is:

$$E(y|\mathbf{x}) = \mathbf{x}\beta F(z) + \sigma f(z)$$

where $z = X\beta/\sigma$ and f(z) is the unit normal density and F(Z) is the normal CDF.

Furthermore, the expected value of y for observations above the limit, $y > 0$, is $\mathbf{x}\beta$ plues the expected value of the truncated normal error term (see McDonald & Moffitt 1980 and Ameniya 1973):

$$\begin{aligned} E(y|\mathbf{x}, y > 0) &= E(y|\mathbf{x}, u > -X\beta) \\ &= \mathbf{x}\boldsymbol{\beta} + \sigma\frac{f(z)}{F(z)} \end{aligned}$$

Thus, we can re-write $E(y|\mathbf{x})$ as:

$$E(y|\mathbf{x}) = F(z)E(y|\mathbf{x}, y > 0)$$

Taking the partial derivative wrt. to X_j gives:

$$\frac{\partial E(y|\mathbf{x})}{\partial x_j} = F(z)\frac{\partial E(y|\mathbf{x}, y > 0)}{\partial x_j} + E(y|\mathbf{x}, y > 0)\frac{\partial F(z)}{\partial x_j} = F(z)\beta_j$$

which we re-write as:

$$\frac{\partial E(y|\mathbf{x})}{\partial x_j} = P(y > 0|\mathbf{x})\frac{\partial E(y|\mathbf{x}, y > 0)}{\partial x_j} + E(y|\mathbf{x}, y > 0)\frac{\partial P(y > 0|\mathbf{x})}{\partial x_j} = P(y > 0|\mathbf{x})\beta_j$$